THE DEVELOPMENT OF AN ECONOMICALLY VIABLE BIOMASS FEEDSTOCK SUPPLY CHAIN TO MEET THE RENEWABLE FUEL STANDARDS

A Dissertation

by

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ABSTRACT

This dissertation addresses the challenge to develop an economically viable biomass feedstock supply chain (SCh) that is able to provide feedstock under a range of operating conditions and meet the national targets for cellulosic fuels. This goal requires improvements on the structure of the feedstock logistics and the unit operations utilized to collect biomass. An assessment of the underlying assumptions for the range of conditions across the United States (US) was performed to determine their influence on perennial grasses predicted by the Department of Energy (DOE). Potential perennial grass production was overestimated in 2011 nationwide by 8-11% and 36-87% in Texas. These overestimations are still present in the 2016 report, as perennial grasses are still predicted to grow on cropland with low rainfall levels. The revised total herbaceous biomass predicted exceeded the national targets, but the geographical location of biomass production changed. Overestimating biomass affects sustainability policies and planning. The revised predictions were used to determine the location of collection facilities for biomass and quantify potential accessible and economically stranded herbaceous biomass in the US. Of the total nationwide available biomass, 78% could be accessed by biorefineries and 12% by depots, leaving 10% as stranded biomass. In total, 161 million Mg (Megagrams) year^{-1} of feedstock delivered to 77 biorefineries (with capacities >2,000 Mg day^{-1}) around the US and 22.7 million Mg year^{-1} delivered to 171 depots (with capacities >240 Mg day^{-1}). Overall, 65.3 billion liters of advanced biofuels, enough to meet the 60 billion liter target of advanced cellulosic biofuel. A simulation tool was developed to evaluate an experimental module-based biomass collection system of corn stover in Texas and Iowa and of switchgrass in Iowa and Tennessee, the BioMass Optimized Delivery System (BioMODS). Considering a grower payment of $ 29.77 DMg^{-1}, BioMODS costs were $90.82 and $71.63 for corn stover in Texas and Iowa; and, $69.19 and $66.29 for switchgrass in Iowa and Tennessee. The BioMODS system met the DOE goal of $88.2 DMg^{-1} and was proven more cost-effective than some studies presented by DOE (with the exception of the Texas case study).

DEDICATION

In loving memory to my grandmother, Justa Segovia de Loo, who was able to be the flower girl at my wedding a month before her departure. I wish you were still here to celebrate this accomplishment with me.

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Contributors

All work for the dissertation was completed by the student, under the advisement of Dr. Stephen Searcy of the Department of Biological & Agricultural Engineering. This research was supervised by a dissertation committee consisting of Dr. Stephen Searcy, Dr. Ronald Lacey and Dr. Sergio Capareda from the Biological & Agricultural Engineering Department and by Dr. Wilbert Wilhelm from the Industrial and Systems Engineering Department at Texas A&M University.

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NOMENCLATURE

all25	Scenario name of POLYSYS model run, details in Chapter III
BGY	Billion Gallons per Year
BT2	US Department of Energy's Second Billion Ton Study in 2011
BT16	US Department of Energy's Third Billion Ton Study in 2016
CBS	Conventional-Bale System
CDL	Cropland Data Layer
CFLP	Capacitated Facility Location Problem
CS	Corn Stover
DMg	Dry Matter in Mega grams
DMT	Dry Matter in Tons
DOE	US Department of Energy
EC	Energy crops
Eff	Efficiency
ESRI ArcMap®	Geographic Information System Software Package for Analysis and Manipulation of Geospatial Data
FLP	Facility Location Problem
GGE	Gasoline Equivalent Gallons
GIS	Geographic Information System
Ha	Hectares
Hp	Horsepower

Hr	Hours
IA	Iowa
IDay	Current day
IHour	Current hour
INL	Idaho National Laboratory
Kg	Kilograms
Lb	Pounds
MC	Moisture content (wet basis)
Mg	Mega grams
NASS	National Agricultural Statistic Service
NP-hard	Non-Deterministic Polynomial-Time Hard Problem
NP-problem	Non-Deterministic Polynomial-Time Problem
NREL	National Renewable Energy Laboratory
OBP	US Department of Energy's Office of the Biomass Program
past100	Scenario name of POLYSYS model run, details in Chapter III
POLYSYS	Agricultural Policy Analysis System, economic simulation model – University of Tennessee
RFS2	U.S. Environmental Protection Agency Renewable Fuel Standard of 2007
SCh	Supply Chain
SW	Switchgrass
TN	Tennessee

TNRIS	Texas Natural Resources Information System
TX	Texas
UFFS	Uniform-Format Feedstock System
USDA	United States Department of Agriculture
WS	Wheat Straw

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CHAPTER I

INTRODUCTION

Background

Several studies in academia, government and industry sectors focus on the feasibility of increasing renewable energy production in response to the Energy Independence and Security Act (EISA) of 2007. Current biofuel production in the US relies primarily on corn grain conversion to ethanol, which is considered the first-generation biofuels. The Renewable Fuels Standards (RFS2), proposed by the Environmental Protection Agency (EPA), mandates that starting in 2016, all of the increased production in renewable fuels must be met with advanced (or second-generation) biofuels, such as cellulosic ethanol and other biofuels from feedstock other than corn starch. The production of renewable transportation fuels would displace conventional imported petroleum use and, consequently, decrease US dependence on foreign oil and offer a clean-burning alternative. One of the most significant challenges to accomplishing the long-term biofuel production goals is the ability to be price competitive against fossil fuels, particularly petroleum.

The RFS2 has set a targeted production of 57 billion liters year^{-1} (15 billion gallons year^{-1} (BGY)) of conventional renewable transportation fuel (such as corn grain based fuel) and 79 billion liters year^{-1} (21 BGY) of advanced biofuels by 2022, of which at least 60 billion liters year^{-1} (16 BGY) must be some type of cellulosic biofuel.

The national ambitious goal for a clean-burning fuel alternative proposes that the American agriculture not only produce food, feed and fiber, but also feedstocks to supply the rapid growth in demand for cellulosic feedstock over the next few decades. The American freight transportation infrastructure will have to support the addition of 170 DMg (188 million DMT) by 2022, assuming a generalized conversion rate of 355 liters DMg^{-1} (85 gallons DMT^{-1}) (US DOE, 2010). To put this magnitude into perspective, the national rail system will have to support an additional 1.68 million jumbo rail hoppers (102 DMg per rail-hopper) or the national highway system will have to support an additional 7.24 million large semi-trucks (23.6 DMg per truck) by year 2022. In addition to the stress of adding such high number of railcars or trucks to the transportation network, the distances that biomass will travel is uncertain and will greatly depend on the supply chain (SCh) design that the industry adopts. The decisions on how to best support all the agricultural roles and allocate agricultural lands are vital to the US and hence, extended research has been performed on this topic.

Biomass feedstock logistics, which include activities such as harvesting, transporting, and preprocessing, collectively represent one of the greatest challenges to the success of the biofuel industry (Fales et al., 2007). Feedstock SCh costs encompasses 8% of the total grain-based ethanol production costs (Hess, Wright, and Kenney, 2007). In contrast, the supply-system for cellulosic ethanol accounts for 35-65% of the total production cost for the cellulosic ethanol industry (Fales et al., 2007; Hamelinck et al., 2005; Kumar and Sokhansanj, 2007). This difference in production is, in part, because the corn-based ethanol industry is already established while the cellulosic ethanol industry is still an emerging industry. According to Hess et al., logistical costs that exceed 25% of the total biomass value leave very little room for profit for biomass producers and biorefineries (2007). To reduce these costs, improvements to the entire value-chain from harvest through transport and to the bio-reactor throat are required. A higher density feedstock with desirable flow characteristics is fundamental to optimize its collection and handling activities, reduce total energy use, and maximize the revenue of the industry (Fales et al., 2007). Given that the national Biomass Program strategy has already determined the starch-based ethanol (corn grain based) as a well-established commodity fuel, research has recently switched focus to introducing alternative fuels, such as advanced and cellulosic biofuels (non-food based fuels) into the marketplace.

The US Department of Energy (DOE) has published three strategic assessments of the potential biophysical availability of biomass: the 2005 Billion-Ton Study (BTS) (Perlack et al., 2005), the 2011 Billion-Ton Study Update (BT2) (Perlack et al., 2011) and the 2016 Billion-Ton Report: Advancing Domestic Resources for a Thriving Bioeconomy (BT16) (US DOE, 2016b). These reports build on each other with the most recent data available and present the analysis of the nation's resources (agricultural and forest) capability to sustainably produce at least 907 million dry Mg (one billion dry tons) of biomass annually. These nationwide biomass inventories provide a means to predict the development of the industry while overcoming the logistic challenge of biofuels.

In this dissertation, the term "biorefinery" refers to the conversion facility for cellulosic biomass to transportation liquid fuels, or biofuels. The term "depot" is used for facilities used as storage and value-adding to biomass feedstock. Depots are an intermediate location between fields and biorefinery. Many pioneer biorefineries will rely on local supplies of baled biomass. This assumption, combined with the dispersed nature of biomass and its generally low density, has caused most feedstock SCh investigations to focus on trucks as the primary mode of transport. An expansion of an economic competitive cellulosic biofuel industry will require cost reductions in feedstock production, an efficient feedstock SCh, adequate cellulosic conversion technologies and policy initiatives that would help overcome the infancy and inherent inefficiencies of the cellulosic biomass industry. This research addresses the inefficiencies of the SCh for cellulosic biomass by taking advantage of economies of scale to compete with fossil fuels.

In addition to the issue of logistical systems, the properties acquired by densifying biomass introduce the option of incorporating high-capacity transport alternatives (such as rail and barge) for long hauls. Rail and barge modes of transportation offer lower costs for longer hauls and higher volumes of bulk commodity and, use lower energy per unit of transport (consequently, lower greenhouse gas emissions) when compared to truck transportation (Gonzales et al., 2013). High-capacity transportation modes are generally more cost efficient than trucks for longer hauls and higher volumes of bulk commodity. However, raw, unprocessed biomass (i.e. as collected from the land) is not in a format suitable for handling by rail and barge (Gonzales, 2012). The use of high capacity transportation modes would greatly expand the potential collection radius of the biorefinery, reducing feedstock supply risk and introducing more resources into the biomass market (Gonzales, 2012).

The uniform-format logistics model vision presented by the Idaho National Laboratory includes the addition of depots in the bioenergy SCh. This vision is for a national biomass market that would provide a buffer against supply upsets, biomass price, and quality due to a number of factors (e.g. feedstock collection radius for biorefineries, natural disasters). The combination of the substantial investments necessary to institute a biorefinery and the biomass supply uncertainty inherent of agricultural products make owner/operators risk averse and reluctant to scale up refineries. Including depots as part of the SCh expands the feedstock collection radius of a biorefinery, hence allows for larger biorefineries. Larger biorefineries can take advantages of economies of scale, which can result in cost-per-unit output savings. Shortages caused by biomass supply uncertainties can be overcome by a larger supply area which provides a more stable and sustainable feedstock supply. The incorporation of depots can also enable farmers to participate in the added-value process at the depots, a similar concept as co-operative elevators in the grain industry. There is an evident need to improve the new and inherently inefficient cellulosic industry for biofuels to be cost competitive with fossil fuels. Actions to promote, foster and sustain the development of a cellulosic bioeconomy are needed in several focus areas (resource assessment, agronomic systems, crop development, feedstock supply logistics, education and extension) to meet the policies stated in the RFS2 (Fales et al., 2007).

Objectives

Ongoing research at Texas A&M University has the goal of developing an economically viable biomass feedstock SCh that is able to provide feedstock under a range of operating conditions. Achieving this goal requires advances on a number of topics related to the structure of the feedstock logistics and the unit operations utilized to collect the biomass. The following three research objectives addressed in this dissertation contribute to achieving this stated goal.

1. Assess the underlying assumptions for the range of conditions across the US and determine their influence on perennial grasses predicted in the Billion-Ton Studies.
2. Determine the likely structure of the biomass feedstock SCh and quantify the potential accessible and economically stranded herbaceous biomass from different scenarios of predicted available biomass in both TX and the US.
3. Develop a simulation tool for assessing the relative performance and delivered feedstock cost of an experimental module-based biomass collection system in comparison to commercially available alternatives.

Chapters II, III and IV present the literature review, datasets and methodologies. used, and the results obtained from addressing the three objectives of this dissertation.

Motivation

The national estimates of biomass inventories presented in the BT2 need to be verified on a regional basis to ensure that energy crops are only predicted to grow on lands with enough precipitation for a sustainable rain-fed production. A reliable resource assessment helps determining which of the SCh structures envisioned in the literature review, the conventional-bale model or the uniform-format model, will prevail or if a combination of them will be the best fit. While raster-based assessments of biorefinery location are present in the literature review, to the author's knowledge, there is no raster-based published study that analyzes the state of TX given the estimates of the BT2. Finally, expanding the IBSAL model to incorporate the analysis of module-based biomass collection will greatly contribute to the literature review of the biomass SCh and the module-biomass unit format could potentially decrease the logistics cost of biofuels.

CHAPTER II

ASSESSMENT OF PREDICTED PERENNIAL GRASS INVENTORIES*

Background

The US DOE's nationwide biomass inventory reports, the BTS, BT2 and the BT16 (Perlack et al., 2005; US DOE, Perlack et al. ,2011; US DOE, 2016a) are a combined effort from the industrial, academic and government sectors that have identified sufficient biomass resources to meet the volumetric requirements of the EISA. However, when the published data is mapped on a county-by-county basis, questions were raised regarding the estimated land-use changes for perennial grasses. Specifically, high quantities of perennial grasses were forecasted in counties with low average annual precipitation. In addition, these resources are widely distributed in rural areas, and can be distant from the existing fuel and transportation infrastructure and remote from where population densities are high. The majority of the population lives in the East and West US; however, the majority of the biomass is available mainly in the Midwest and South (Gonzales et al., 2013).

The feedstock used for cellulosic biofuels includes crop residues, annual energy and perennial energy crops (EC). The collection of crop residues for bioenergy must be limited to protect the soil from erosion, retain moisture and maintain, or increase,

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organic matter and nutrients. Annual EC will most likely be established in cropland as an alternative crop in rotations. Switchgrass (*Panicum virgatum*), the most promising perennial biomass crop in the US, can be established on marginal land such as pastureland because of its inherent resistance to drought and heat (Gunderson et al., 2008).

The study presented in this chapter is an assessment of the herbaceous biomass predicted in the BT2. This work was completed before the release of the BT16 report. While some of the changes in land-use assumptions suggested by this work were included in the BT16 analysis, not all were. All estimates of potential biomass within the contiguous US were obtained through the Policy Analysis System (POLYSYS) agricultural modeling framework, and were based on various assumptions regarding current and future inventory, production capacity, availability, and technology. We provide details of the underlying assumptions that are not explicitly described in either of the DOE-sponsored reports. Our original focus was to compare our findings with the BT2 inventory estimates, but, we have extended our comparison to include BT16.

The objective of this study was to assess the underlying assumptions for the range of conditions across the US and determine their influence on total herbaceous biomass predicted. Our goal was to examine the influence of those POLYSYS assumptions on the predicted biomass production (particularly for perennial grasses) and to examine the change in production estimates under alternative assumptions. A reliable resource assessment, at both national and county levels, is paramount to calculate realistic estimates of future feedstock supplies. The units used for biomass in the DOE reports were US short tons, but units were converted to mega grams (Mg) to avoid confusion with long tons or metric tonnes.

Literature review

In 2005, DOE and US Department of Agriculture (USDA), published the BTS, to determine if the contiguous US agriculture and forest resources could sustainably produce at least 907 million dry Mg (DMg) of biomass annually (Perlack et al., 2005). Price was not a restriction to identify potentially available agricultural and forestry resources in the 2005 BTS. For that reason, a portion of the estimated potential biomass in the report was foreseen as too expensive to be economically viable. This and additional perceived shortcomings of the 2005 BTS were addressed in the BT2 (Perlack et al., 2011). Specifically, the updated report included a county-by-county biomass inventory of primary feedstocks, analyzed available biomass based on several farmgate prices (between \$44.09 and \$88.18 DMg^{-1} with \$5.51 increments - all prices presented in this chapter are in 2011 US dollars) for the individual feedstock, and included a more rigorous treatment and modeling of resource sustainability. Farmgate price was defined as a basic feedstock price that includes cultivation (or acquisition), harvest, and delivery of biomass to the field edge or roadside in the BT2, excluding on-road transport, storage, and delivery to an end user. Baling activities are included in the farmgate price for grasses and residues. The BT16 builds on the research presented in the BT2 and includes updates on the farmgate analysis using the latest available data. The latest DOE report introduces the cost of transportation to biorefineries under specified logistical assumptions in the analysis (US DOE, 2016a). All three reports identified sufficient biomass resources to meet the volumetric requirements of the EISA.

Assumptions on current and future macroeconomic conditions, policies, and weather were grounds for assessments (Westcott, 2010). The predicted values in the DOE assessments were obtained through the POLYSYS agricultural modeling framework. POLYSYS simulates changes in policy, the economy and/or resource conditions and estimates the resulting impacts for the US agricultural sector (De La Torre Ugarte and Ray, 2000). POLYSYS quantifies potential crop residue as a function of crop yield, moisture content, residue to grain ratio and crop residue production and collection cost while accounting for soil protection. Reliable and realistic estimates of future feedstock supplies are key for business planning and policy development for the expansion of a sustainable biofuels industry.

DOE estimations of biomass feedstock are published in the Bioenergy Knowledge Discovery Framework (KDF) (ORNL, 2010). Given that the scope of the assessments were on a national level, the land-use change assumptions may not represent the realities of all states when evaluating on a county-by-county basis. When the published BT2 predictions for biomass are mapped on a county-by-county basis (Figure 1 (a)), the predictions of perennial grasses for the states that bisect the 100th meridian were questioned based on the knowledge of local conditions in TX. High quantities of perennial grasses were forecasted in counties with low average annual precipitation despite the BT2 assumption that EC will not be established on land requiring supplemental irrigation.

The BT2 evaluated four scenarios: a baseline scenario and three high yield scenarios. The baseline scenario assumes a continuation of the USDA 10-year forecast for the major food and forage crops and an extension to year 2030. The baseline scenario considers an annual increase of a little over 1% for corn and energy crop yields for the 20-year simulation period. The baseline scenario assumed a total 3% gradual change from conventional corn tillage practices to no-till from year 2009 to 2030 (7% gradual change for wheat). In contrast, the high-yield scenarios were modeled with higher corn yields (1.95% annual increase) and three levels of energy crop productivity increases — 2%, 3%, and 4% yield increase annually. The high-yield scenarios assumed a 31% reduction in conventional corn tillage practices, a 6% decrease in reduced till practices, and a 37% increase in no-till practices from year 2009 to 2030. Similarly, it assumed a 29% decrease in conventional wheat tillage practices, a 17% decrease in reduced till practices, and a 46% increase in no-till practices from year 2009 to 2030. The assumed productivity increase reflects the gains in experience in planting EC and more aggressive implementation of breeding and selection programs. In this study, we focused specifically on the baseline scenario and the simulated year 2022 to evaluate the contribution of these states to the RFS2 targeted goals of 79 billion liters of advanced biofuels for 2022.

Crop hectares per county in the BT2 are estimated from a four-year average of survey data from the National Agricultural Statistics Service (NASS). Pasture hectares are based on the 2007 census (USDA NASS, 2009). The scenarios presented in the BT2 also assumed that perennial grasses could be potentially grown on cropland, cropland used for pasture, and permanent pasture, if the market price is sufficient to cause land-use change. Herbaceous energy crops such as switchgrass (SW), miscanthus, energy cane, and biomass sorghum were simulated as individual crops in the BT16, while these were generalized in the categories of perennial grasses and annual energy crops in the BT2. SW was used to model perennial grass in POLYSYS in the BT2 study. The experience gained about SW as hay and forage crop over nearly 80 years indicates that SW will be productive and sustainable on rain-fed marginal land east of the 100th meridian, except for the Pacific Northwest (Mitchell et al., 2005; Mitchell et al., 2013). This experience guided the BT2 in limiting the conversion of pastureland to perennial grasses to counties east of the 100th meridian, except for the Pacific Northwest. However, some of the counties east of the 100th meridian have a low average annual precipitation, which challenges the BT2's assumption about rain-fed sustainable production. Similarly, a rain-fed sustainable production will be challenging with the BT2 allowance for all counties in the US to convert cropland to perennial grasses, regardless of the average annual precipitation in the county. For example, in the baseline scenario at the \$66.14 DMg^{-1} farmgate price in year 2022 a total of 49,532 DMg are predicted to be produced in Borden County, TX, which averages 508 mm (20 in.) annually. Thus, it is important to address the land-use change assumption for perennial grasses as the assumption greatly impacts the resulting inventories.

Successful establishments of SW production can be grown west of the 100th meridian with irrigation (Washington State University, 2009). Likewise, a compilation of published literature on 1,190 observations for SW yields of lowland and upland ecotypes grown at 39 field sites across the US concluded that precipitation limits yield west of the Great Plains (Wullschleger et al., 2010). Most of the observations of lowland cultivars analyzed by Wullschleger et al. were planted in the south, whereas, the upland SW ecotypes were planted across the full range of latitudes. Wullschleger et al. (2010) and Heaton et al. (2004) concluded that there is a positive response of yield to precipitation and nitrogen. But, in contrast to Heaton's analysis, Wullschleger et al. concluded that biomass yields did increase with higher temperatures up to a point and then decreased. The response patterns suggested a broad optimal temperature, hence the study by Wullschleger et al. was not able to completely explain the yield response to temperature. Song et al. (2014) used the Integrated Science Assessment Model (ISAM), a land surface model, to estimate and simulate spatial and temporal variations of two SW cultivars, Alamo and Cave-in-Rock between 2001 and 2012. The study identified four spatial zones defined by historical average yield and temporal yield variance in eastern US. Their results suggest that high yields are supported by high precipitation (>600 mm), moist soil condition, temperatures less than 23 °C, and longer mean photoperiod during the vegetative stage. Song et al. indicated that the annual median accumulated precipitation averaged over 2001 and 2012 was 669 and 603 mm (26 and 24 inches) for Cave-in-Rock in high and low yield zones, respectively. Similarly, this environmental factor was 754 and 610 mm (30 and 24 inches) for Alamo in high and low yield zones.

The state of TX is one of the states bisected by the 100th meridian; hence, we aimed our attention to this state. Sanderson et al. (1999) evaluated several SW cultivars and germplasms for biomass feedstock production in TX and determined that rainfall amount was the predominant factor affecting SW productivity in the TX locations studied (Beeville, College Station, Dallas, Stephenville, and Temple). The extreme drought of 1995 (517 mm) and 1996 (544 mm) precluded harvestable growth in Beeville. In 1996, the total rainfall in College Station (762 mm) reduced SW yields by 52% from the average yield in 1995 (1042 mm). The severe drought of 1995 (924 mm) and the first 9 months of 1996 reduced Dallas SW yields by 32% and 77% in 1995 and 1996 from the yields in 1994 (1459 mm). The rainfall late in 1996 benefited the average yield in that year. The average yield in Stephenville reduced by 10% in 1995 (896 mm) and by 47% in 1996 (845 mm) from 1994 yields (999 mm). The drought in 1995 (650 mm) and in 1996 (795 mm) reduced the average yields by 32% and 77% from yields in 1994 (958 mm) in Temple. The study concluded that Alamo is the best-adapted commercially available SW cultivar for biomass feedstock production in TX. Muir et al. (2001) analyzed the yield and stand responses of Alamo SW in TX during 1992 to 1998 and suggested a southern limit of adaptation for Alamo between Stephenville, TX (32.22◦N) and Beeville, TX (28.4◦N) that is not related to rainfall or soil type since average rainfall is similar in both sites. In addition, at latitudes above 38.2◦N, lowland cultivars exhibit a decrease in yield at a rate of about 12.5% per degree latitude (Wullschleger et al., 2010).

The DOE’s most recently published comprehensive effort to estimate the biomass inventories in the US is the BT16. The BT16, as well as the BT2, was derived from a series of nationwide assumptions built into the POLYSYS framework, including non-irrigated perennial grass production. The moisture limit for the BT2 study was based on a geographic landmark, the 100th meridian. Productivity, as a function of precipitation, brings into question the use of the 100th meridian. The literature suggests that a minimum precipitation rate adequate for successful production of SW is between 610 and 660 mm (24 and 26 inches). The BT16 study revised the land-use geographic limit for conversion of pastureland to perennial grasses and replaced it with a precipitation constraint. The difference between the land-use assumptions in the BT2, the BT16 and the ones applied in our study are discussed below.

Datasets and methodology

Detailed data for perennial grasses, not made publicly available in the KDF, were obtained from Oak Ridge National Laboratory (ORNL) to understand the different land types where growth of perennial grasses was predicted in the BT2. Perennial establishments on cropland, cropland pasture and permanent pasture are illustrated in Figure 1(b-d). The data illustrates the conversion boundary at the 100th meridian on pastureland (both cropland pasture and permanent pasture), but not for cropland conversion to perennial grasses.

We evaluated the inclusion of county-based average annual precipitation to replace the 100th meridian. Influenced by the literature, we analyzed biomass inventories based on a 635 mm (25 inch) cutoff for the conversion of land to perennial grasses. Figure 2 delineates the average annual precipitation for each county in the contiguous US based on data from 1981 to 2010 (PRISM Climate Group, Oregon State University, 2004). Note that the map indicates that the 635 mm precipitation mark and the 100th meridian line up in TX, Oklahoma, Nebraska and Kansas, but not in South and North Dakota. Hence, perennial grasses estimated to be grown on cropland west of the 100th meridian in the BT2 might require irrigation given the low average annual precipitation (lower than 635 mm). Discussion with ORNL staff led to the conclusion that county-based average annual precipitation data is a better indicator for perennial grass potential than the 100th meridian used in the BT2.

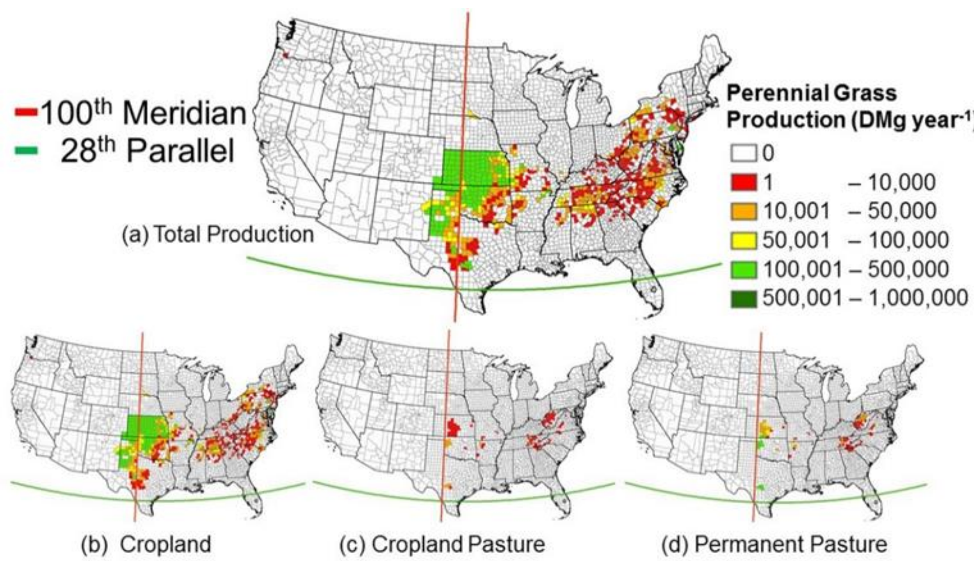

Figure 1 BT2 Perennial grass production for 2017 at the farmgate price of \$55.12 DMg^{-1}.

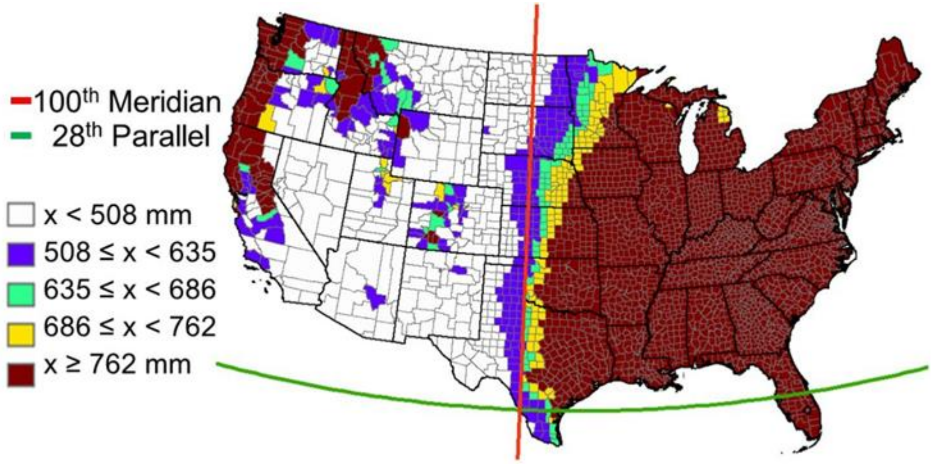

Figure 2 PRISM county average annual precipitation (mm).

ORNL staff provided us with access to a version of the POLYSYS model to generate new predictions for biomass with the 635 mm average annual precipitation mark in place of the 100th meridian boundary. The approach aimed to ensure that production of perennial grasses will occur on lands with at least 635 mm of precipitation, based on the 30-year PRISM normal precipitation study. The replacement of the 100th meridian with the 635 mm boundary resulted in a reduction of 2.55 million hectares of total available pastureland (from 47.4 and 2.79 million ha of permanent pasture and cropland pasture to 44.9 and 2.74 million ha, respectively) (USDA NASS, 2012). South Dakota and North Dakota were the states most affected by this change. In South Dakota, the total permanent pasture and cropland pasture was reduced by 87% (from 1,995,704 ha) and 84% (from 76,480 ha), respectively. As illustrated in Figure 2, none of the counties in North Dakota has an average annual precipitation greater than or equal to 635 mm. Thus, a reduction from 858,145 ha of permanent pasture and 31,972 ha of cropland pasture to zero hectares of total pastureland (permanent and cropland) was observed.

A speculation can be made that 635 mm of average annual precipitation might not be enough for a sustainable production of perennial grasses. The scope of this study was limited to simulations of the POLYSYS model with the 635 mm precipitation boundary, which resulted in a total national reduction of 5% in available pastureland from the BT2. Figure 2 illustrates the impact on the number of counties that will not be considered for perennial production in the US when using high precipitation thresholds for economically viable yield levels. Placing a 686 mm or 762 mm of average annual precipitation boundary will result in a national reduction of available pastureland of 16% and 27%, respectively. These observations indicate that national biomass production will have a significant sensitivity to the rainfall limits for sustainable SW production.

Following the publication of the BT2, the POLYSYS model has undergone additional improvements, such as the incorporation of the value of time in farmgate prices and updates with the best information available for perennial grass yields, census data and the USDA Baseline. Table 1 illustrates the differences between the POLYSYS version used for the publication of the BT2 report, the one used for this study, and the BT16 report.

Table 1 Comparison of the POLYSYS framework versions.

POLYSYS framework	BT2 version	Version used in this study	BT16 version
USDA baseline	2009	2014	2015
USDA Census	2007	2015	2012
Switchgrass yields	2010	2014	2014
First year simulated	2009	2014	2015
Simulated year examined	2017	2022	2023

Since nearly all dedicated bioenergy feedstocks have insufficient information from which to extrapolate yield nationwide (Miguez, Maughan, Bollero, and Long, 2012), the Sun Grant Western Region GIS Center (PRISM Climate Group) at Oregon State University developed the PRISM environmental model (PRISM-EM) (Halbleib, Daly, and Hannaway, 2012). As opposed to extrapolating plot/field yield data to larger regions, PRISM-EM is based on a limiting-factor approach. The model tracks precipitation, evapotranspiration, and soil moisture depletion and estimates relative yields based on water balance simulations, plant injury curves for summer heat and winter cold, and growth constraints due to soil pH, drainage, and salinity. The county-based perennial grass yields input to the POLYSYS model are the output of the PRISM-EM. Since the publication of the BT2, improvements have been made to the PRISM-EM. Consequently, we used an adjusted SW yield input dataset to the POLYSYS model. Figure 3 outlines the different yield datasets. Figure 3(a) exhibits the perennial grass yields used in the BT2; note that higher yield zones are displayed in eastern Tennessee and Kentucky, and some areas in Georgia, North Carolina and South Carolina. In contrast, the PRISM-EM output in Figure 3(b) and used in this study discloses the highest perennial grass yields in Mississippi, Louisiana, Arkansas, Florida and western

Tennessee and Kentucky. The yields mapped below are mainly for SW and Miscanthus cultivars, except for Florida, where energy cane was assumed to be adopted. The map in Figure 3 (b) illustrates SW yields between 6.72 and 11.21 Mg ha^{-1} (3 and 5 tons acre^{-1}) along southern states bisected by the 100th meridian (Kansas, Nebraska, Oklahoma and Texas) and yields between 4.48 and 6.72 Mg ha^{-1} (2 and 3 tons acre^{-1}) for North and South Dakota. Depending on the latitude, US counties bisected by the 100th meridian are classified as either low and stable or low and unstable yield zones for Miscanthus, Cave-in-Rock upland SW and Alamo lowland SW (Song et al., 2014). Perennial grasses were generalized in a category for simulation in the BT2 and in this study. Switchgrass, miscanthus and energy cane were simulated as individual crops in the BT16.

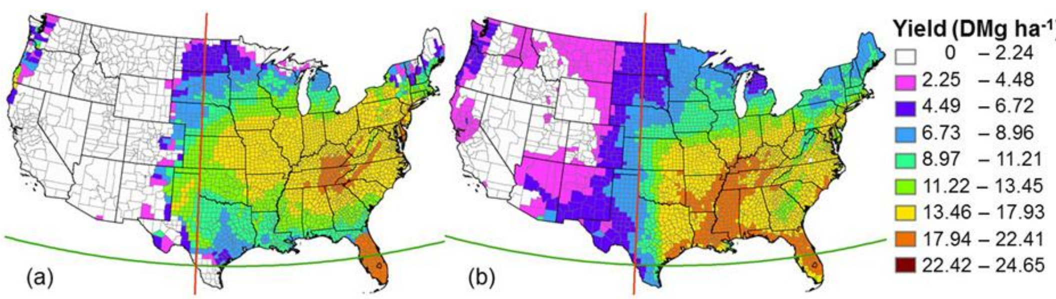

Figure 3 (a) Perennial yields used in the BT2 (b) and in this study.

In addition to the differences between the POLYSYS versions presented in Table 1, the farmgate prices in POLYSYS were updated to reflect real values for every predicted year using the 2016 USDA Long Term Projection GDP price index adjusted values. For simplicity, we present our results in nominal prices as outlined in the BT2 scenarios.

To compare the several changes between versions of the POLYSYS framework, we developed a scenario named past100 with the same boundaries for conversion of land to perennial grasses as the BT2 (expounded in Table 2). Given the five-year difference in simulation periods, we compared predictions for 2017 reported in the BT2 with the data predicted for year 2022 simulated in scenario past100 from this study. The baseline year for the simulations presented in the BT16 was 2015; hence, we compared our results for year 2022 with the BT16 biomass inventories for year 2023 (Table 1). Regression analysis techniques were used to assess the correlation between POLYSYS outputs presented in the BT2 and the outputs developed in this study under the past100 scenario. To evaluate the responsiveness of using the 635 mm average annual precipitation mark in place of the 100th meridian boundary, we developed two additional scenarios: past25 and all25. Scenario past25 only allowed conversion of cropland pasture and permanent pasture on counties with a 635 mm or higher average annual precipitation. Similar to the BT2 assumption, this scenario has no precipitation restriction for establishing perennial grasses on cropland. Conversely, scenario all25 will only allow for conversion of lands (cropland, cropland pasture and permanent pasture) to perennial grasses in counties with a 635 mm or higher average annual precipitation, regardless of land type. It was anticipated that the addition of a precipitation restriction for conversion of cropland would result in a significant decrease of predicted perennial grass nationwide. Figure 4 illustrates the differences between scenarios. The graphic on each outlined area shows the common conditions for each of the six combinations of scenario and land type. The information about which specific counties in the Pacific Northwest were allowed for conversion to perennial grasses in the BT2 was not publicly available. Hence, we assumed an inclusion of counties with an average annual precipitation of 635 mm or higher.

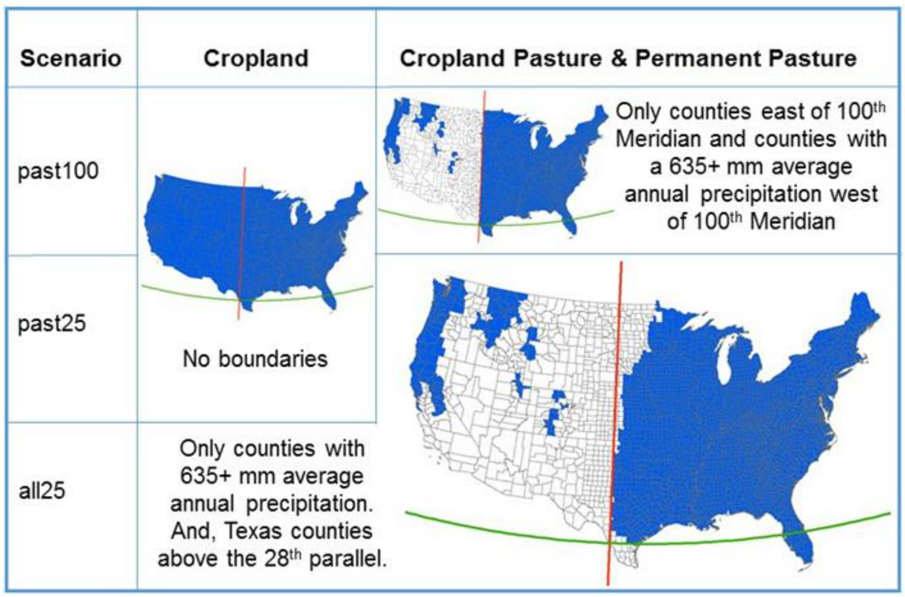

Figure 4 Set of counties allowed for conversion to perennial grasses.

The most comparable of our scenarios, in terms of land-use assumptions, to the BT16 inventories of 2022 was past25. The pastureland in both scenarios was identified to be eligible for conversion to perennial grasses if there was an average annual precipitation greater than or equal to 635 mm. The BT16 analysis does not constrain cropland conversion to perennial grasses. The all25 scenario explored the addition of a precipitation constraint regardless of land type. The authors recognize that these comparisons are not entirely comparable, given that the POLYSYS modeling framework has continued to evolve since the version used in this work.

In our scenario analysis, we excluded the reported inventories of perennial grasses in the counties south of the 28th parallel, given that TX research has suggested that south of the 28th parallel there is a limit of adaptation for SW that is unrelated to rainfall or soil type (Muir et al., 2001). In other words, we expected little or no production of perennial grasses in this area. The only states bisected by the 28th parallel are TX and Florida, but, in Florida, energy cane was the perennial assumed to be adopted, not SW. While the baseline scenario in the BT2 does not reflect any production of perennial grasses on counties south of the 28th parallel, this is not the case for the high yield scenarios in the BT2. Though the scope of this study did not include high yield scenarios, it is important to note that a 28th parallel as a limit for conversion of cropland and pastureland to perennial grasses should be considered for high yield scenarios in TX.

Results and discussion

A comparison of the versions of POLYSIS was made to determine how its biomass predictions changed over time. Figure 5 illustrates the resulting regression equations when comparing the predicted corn stover (CS), wheat straw (WS), perennial grasses and annual EC in each of the versions of POLYSYS. Note that points in the charts are national production totals at each farmgate price between \$44.09 and \$88.18 DMg^{-1} with

$5.51 increments, as presented in the BT2. The regression analysis describes a strong correlation between the two POLYSYS outputs as the lowest R-square value was 0.84, obtained when comparing potential annual energy crop production estimated in the BT2 and past100 scenario. We forced the y-intercept (or the constant term) in the regression equation to a value of zero to evaluate the resulting slope. A slope greater than one (such as for CS), indicates an increase in production with the new version of POLYSYS. Similarly, a slope less than one (such as the one calculated for WS, perennial grasses and annual EC), describes a decrease in predicted biomass. In general, we observed that greater research and commercial experience with CS appear to have improved the responsiveness to price while it has reduced the predicted energy crop production values. Predicted values for WS were observed to have little change between the scenarios.

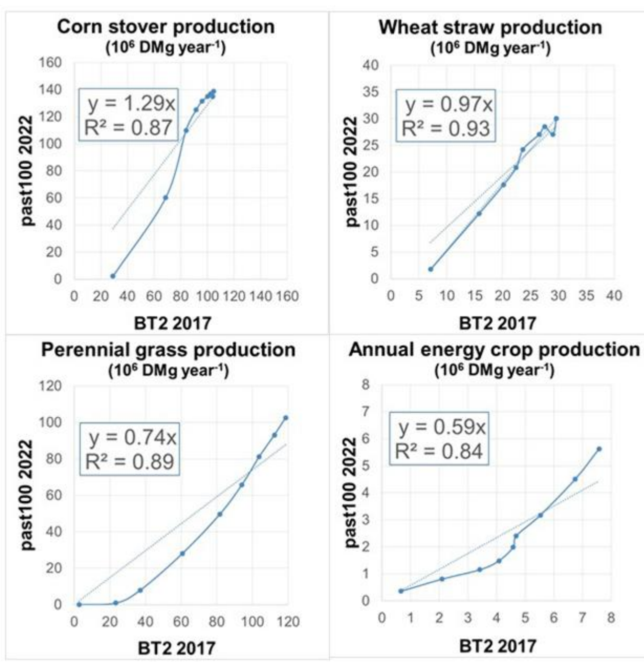

Figure 5 Correlation between major crop's production in the BT2 and scenario past100.

Table 2 illustrates the total US predicted biomass production for major crop residues and energy crops as farmgate price increases from \$44.09 to \$88.18 DMg^{-1}. The differences in predicted values are mainly attributed to the changes presented in Table 1. As expected, with the rise in price, higher production of biomass was estimated in both scenarios. As per Table 2, scenario past100 produces values closer to the BT2 predictions at the \$88.18 DMg^{-1} price than at lower prices. The predicted production for CS, WS and EC presented in Table 2 for the \$44.09 DMg^{-1} price mark value are at least 46% lower in past100 than in the BT2 scenario. With the most recent input to POLYSYS, there was less reliance on CS at lower prices but more reliance on this residue starting somewhere above the \$44.09 DMg^{-1} price. At prices greater than \$55.12 DMg^{-1}, higher amounts for WS are predicted in past100 than in the BT2, yet the change was minimal compared to a CS change. Dependency on energy crop production decreases nationwide in our results when compared to the BT2 results from POLYSYS. In addition, with the new POLYSYS framework setup, production of perennial grasses was almost non-existent at \$44.09 DMg^{-1} price (a nationwide total of 6,069 DMg $year^{-1}$).

Table 2 Differences between production of major biomass crops presented in the BT2 for year 2017 and production simulated for year 2022 in scenario past100.

Farmgate price ($ DMg^{-1})	BT2 for year 2017 (DMg)			
	CS	**WS**	**Annual EC**	**Perennial**
44.09	29,119,088	7,103,166	665,329	2,732,894
55.12	83,962,488	20,154,560	3,413,645	37,026,564
66.14	95,920,453	23,657,654	4,578,834	81,769,278
77.16	102,415,533	27,507,746	5,526,297	103,761,069
88.18	104,826,013	29,616,497	7,572,906	118,591,272
	Percent change from BT2 to past100			
44.09	-92%	-75%	-46%	-100%
55.12	31%	-13%	-66%	-78%
66.14	37%	3%	-57%	-39%
77.16	34%	4%	-43%	-22%
88.18	32%	2%	-26%	-13%

The BT2 report presents all feedstock quantities at the $66.14 DMg^{-1} level since it not only represents a realistic and reasonable price at the time of publication (August 2011) but also it brought in most of the available mass (based on the BT2 results) from all of the simulated feedstock types. The $66.14 DMg^{-1} price was also referred to in the DOE Multi-Year Program Plan cost targets for cellulosic feedstock when adjusted to exclude transportation and handling costs (US DOE, 2012). A more recent version of the Multi-Year Program Plan sets a cost target of $88.18 DMg^{-1}, which includes grower payment/stumpage fee and logistics cost to the throat of the conversion reactor in the form of bales, loose chop, etc. (US DOE, 2014a). In this study, we discuss predicted biomass production for farmgate prices $66.14 and $88.18 DMg^{-1}. Figure 6 is an illustration of the perennial grass predicted in both scenarios at the $66.14 and $88.18 DMg^{-1} price levels. Despite the national decrease in perennial cultivar production between scenarios BT2 and past100 (from 81,769,277 to 49,740,508 DMg at $66.14 DMg^{-1} and 118,591,271 to 102,589,144 DMg at $88.18 DMg^{-1} for each scenario, respectively), the results still predict high production of perennial cultivars east of the 100th meridian (Figure 6).

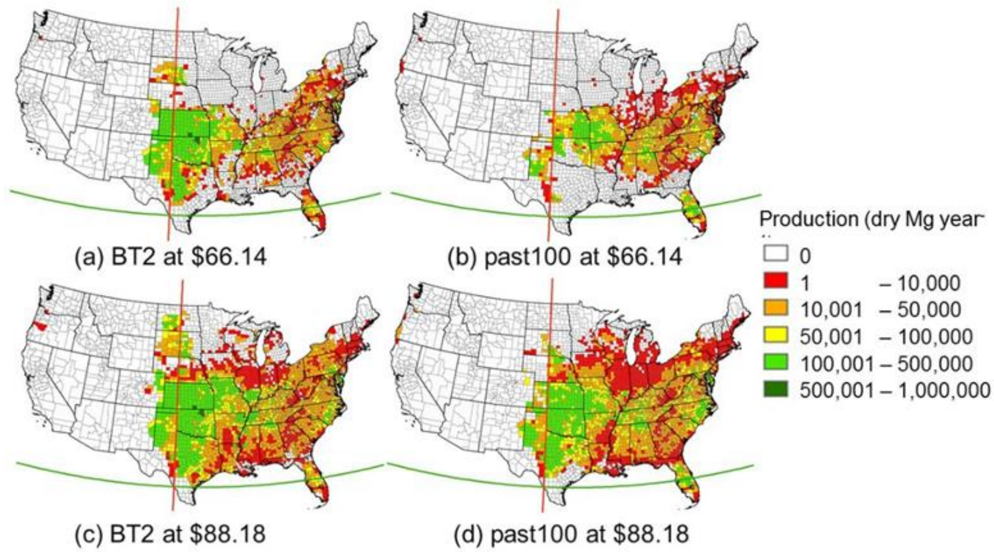

Figure 6 Perennial grass production at the farmgate price of \$66.14 and \$88.18 DMg^{-1} for the BT2 and scenario past100.

Similarly, we evaluated the changes in total perennial grasses estimated to be grown in each scenario: past100, past25 and all25. The comparison of BT2 and past100 illustrates the impact of the updated relationships and databases used by POLYSYS, while the additional comparisons illustrate the effects of substituting the 635 mm precipitation for the 100th meridian (past25), and limiting both pasture and cropland conversions to the 635 mm precipitation limit (all25). When compared to past100, a greater change was observed in total perennial grasses estimated to be grown on cropland for past25 and all25 than perennial grasses estimated to be grown on pastureland (Table 3).

Table 3 National and Texas changes on perennial grass production predictions on pastureland and cropland under each scenario. Past25 and All25 show change in predicted mass compared to Past100.

Farmgate Price ($ DMg^{-1})	Perennial grass on cropland					
	US			TX		
	Past100 (DMg)	**Past25**	**All25**	**Past100 (DMg)**	**Past25**	**All25**
44.09	0	0%	0%	0	0%	0%
55.12	2,618,430	0%	0%	0	0%	0%
66.14	13,315,028	0%	-24%	2,387,597	0%	-99.6%
77.16	30,105,147	0%	-22%	5,389,618	0%	-83%
88.18	42,743,535	0%	-21%	7,444,629	0%	-77%
	Perennial grass on pastureland					
44.09	6,069	0%	0%	0	0%	0%
55.12	5,368,771	0%	0%	0	0%	0%
66.14	36,425,480	-2%	-2%	351,256	0%	0%
77.16	51,034,078	-2%	-2%	4,830,507	-2%	-2%
88.18	59,845,609	-5%	-5%	8,644,382	-1%	-1%
	Total perennial grass					
44.09	6,069	0%	0%	0	0%	0%
55.12	7,987,201	0%	0%	0	0%	0%
66.14	49,740,509	-1%	-8%	2,738,853	0%	-87%
77.16	81,139,225	-1%	-10%	10,220,125	-1%	-45%
88.18	102,589,144	-3%	-11%	16,089,011	-1%	-36%

As per Table 3, a nationwide total of 13,315,028 DMg of perennial grasses were predicted to grow on cropland and 36,425,480 DMg on pastureland in the past100 scenario at the $66.14 DMg^{-1} price for year 2022. A 24% decrease in total perennial predicted to grow on cropland was observed when comparing past100 with scenario all25 and no change from past100 in past25. In both scenarios, past25 and all25, there was an observed decrease of 2% in total perennial predicted to grow on pastureland. Greater amounts of perennial grass were estimated to grow on pastureland at the higher price of $88.18 DMg^{-1}, but lower amounts of perennial on cropland. A 21% decrease in total perennial predicted to grow on cropland in scenario all25 was observed and no change in past25. Again, both scenarios, past25 and all25, simulated a decrease of 5% in total perennial predicted to grow on pastureland. As expected, most of the changes in biomass production between the scenarios studied were in the states that are bisected by the 100th meridian. We focused on the state of TX to evaluate the variation in biomass production. In scenario past100 at the \$66.14 DMg^{-1} price for year 2022, the total perennial grass predicted to grow on cropland and pastureland in TX was 2,387,597 and 351,256 DMg $year^{-1}$, respectively. A major change was observed in perennial grass values estimated to be grown on cropland in the all25 at this price level, a decrease of 99.6% (resulting in a total of 9,051 DMg $year^{-1}$), or nearly a complete elimination of cropland conversion. At \$88.18 DMg^{-1}, the past100 scenario predicted total perennial grass of 7,444,628 DMg $year^{-1}$ on cropland in TX and 8,644,382 DMg $year^{-1}$ on pastureland. Only a 1% decrease was observed in past25 and all25 when compared with scenario past100. The all25 scenario showed a decrease of 77% from past100. Based on the results of the BT2, past100 and past25 scenarios, the state of TX was estimated to produce 6% of the total perennial grasses in the US at \$66.14 and 16% at \$88.18 DMg^{-1}. However, when limiting cropland conversion to counties with a minimum of 635 mm annual precipitation (scenario all25), the TX portion reduces to 1% and 11% for these prices. In the most recent DOE-sponsored report of inventories of biomass, the BT16, the average annual precipitation as a bound for conversion of pastureland to perennial grasses was incorporated. Table 4 presents the perennial grass inventory results from the BT16 and quantities of perennial grass estimated to be grown in drier counties (less than 635mm of average annual precipitation). As in the BT2, the detailed data for perennial grasses established on cropland was not made publicly available in the KDF and were obtained from ORNL staff after the publication of the BT16. Note that in this table we did not present quantities for perennial grasses grown on pastureland for BT16 as our focus was on perennial grasses production estimates for cropland in low-precipitation counties. As understood from Table 3, there is no change in perennial quantities expected to be grown in cropland between scenario past100 and past25. Observe that scenario all25 is not presented in Table 4 because, in this scenario, no quantities were predicted in dry counties at any of the price levels. The values in Table 4 reflect that even in the most recent DOE-sponsored report; perennial crops are expected to be grown on lands with low-precipitation. In addition, significantly higher amounts of perennial production were predicted in the BT16 when compared to the results of our runs, which might make the results for perennial production in BT16 less reliable than in our results. This high increase could be explained by changes in the POLSYS model assumptions related to the other energy crops or crop residues that made perennial production more profitable. Note that perennial grass inventories in the BT16 become inelastic to price at higher prices; and, at higher prices, less perennial grass is estimated to be grown on dry counties' cropland when compared to scenarios past100 and past25.

Table 4 National and Texas biomass inventories presented in the BT16 for year 2023 and perennials on cropland with precipitation less than 635mm.

Region	Farmgate price ($ DMg^{-1})	Perennial on cropland with precipitation <635mm (DMg)		
		BT16	Past100	Past25
US	44.09	192,990	0	0
	55.12	10,396,668	1,284,324	0
	66.14	19,441,233	4,520,010	3,211,019
	77.16	27,199,031	5,735,118	6,891,152
	88.18	33,783,821	6,131,201	9,173,294
TX	44.09	17,984	0	0
	55.12	3,403,037	713,827	0
	66.14	5,066,287	2,133,803	2,378,546
	77.16	5,298,280	2,341,951	4,499,259
	88.18	5,262,935	2,253,024	5,762,765

The total herbaceous biomass predicted in the US (CS, barley straw, sorghum stubble, oat straw, WS, annual EC and perennial grasses) for each of the scenarios discussed are presented in Table 5. At low prices, the US total herbaceous biomass predicted in the BT2 was higher than in the past100 scenario (784% and 6% higher at \$44.09 and \$55.12 DMg^{-1}, respectively). No significant change was observed between the past100, past25 and all25 scenarios at low prices. Conversely, at prices greater than or equal to \$66.14 DMg^{-1}, the total herbaceous biomass predicted in the US was higher in past100, past25 and all25 than in the BT2 scenario and a small reduction (of 4% at most) was observed from past100 to past25 and all25. These differences are attributed to higher predicted amounts of CS and WS nationwide with the updated information and new version of POLYSYS. When comparing the BT2 scenario with past100, past25 and all25, the total herbaceous biomass estimated for the state of TX decreased by up to 75% (at \$66.14 DMg^{-1} from BT2 to all25) and a drop of up to 37% (from past100 to all25 at \$66.14 DMg^{-1}) was observed from past100 to past25 and all25.

While the US total herbaceous biomass predicted in this study is close to the biomass predicted in the BT2 at prices greater than or equal to \$55.12 DMg^{-1}, the geographical location of the biomass changed across the nation. TX is a good example of this geographical difference. The incorporation of improved yield estimates and the other upgrades to the POLYSYS framework resulted in production estimates being more sensitive to price than was found in the BT2 study. Assuming a generalized conversion rate of 355 liters DMg^{-1} (85 gallons DMT^{-1}) (US DOE, 2011a) and based on the scenarios presented, at a price of \$66.2 DMg^{-1}, there is sufficient herbaceous biomass to produce 73 billion liters of cellulosic biofuels, exceeding the RFS2 minimum target of 60 billion liters.

Table 5 Total available herbaceous biomass in the US and TX for each scenario ($DMg\ year^{-1}$).

Region	Farmgate Price (\$ DMg^{-1})	BT2 ($DMg\ year^{-1}$)	Past100 ($DMg\ year^{-1}$)	Percent change from past100	
				Past25	All25
US	44.09	40,751,646	5,195,016	0%	0%
	55.12	146,805,715	138,466,706	0%	0%
	66.14	208,378,702	209,338,491	-0.3%	-1.8%
	77.16	241,528,865	251,753,601	-0.4%	-3.0%
	88.18	262,715,167	279,019,914	-1.0%	-4.0%
TX	44.09	441,799	443,329	0%	0%
	55.12	8,527,809	3,072,096	-1.5%	-1.5%
	66.14	16,384,301	6,484,475	0%	-37%
	77.16	20,788,955	14,196,803	-0.7%	-32%
	88.18	22,948,599	19,990,127	-0.5%	-29%

Given that the BT2 assessment scope was of a national level, the land-use change assumptions may not represent the realities of all states. Changing the 100th meridian boundary to the precipitation boundary was considered to be a better approach to estimate the inputs to the POLYSYS model. Maintaining the DOE assumption that energy crops would not be produced with irrigation should require croplands in low rainfall counties to be eliminated as potential perennial grass production units. The revised inventories for crop residues, annual EC and perennial crops can be used to determine the structure of the likely biomass feedstock SCh that may develop in TX and estimate the portion of the total biomass produced that may be economically stranded.

Conclusions

Potential perennial grass production in the US and TX was likely overestimated in DOE's Billion-Ton Update (BT2) by 8% and 87% at \$66.14 DMg^{-1}, and 11% and 36% at \$88.18 DMg^{-1}, respectively. These over-estimations were due primarily to allowing cropland conversion to perennial grass production under rainfall levels proven to be inadequate for economically sustainable yields without supplemental irrigation. Texas' contribution to the national perennial grass production was found to be 1% and 11% at \$66.14 and \$88.18 DMg^{-1}, as opposed to the reported 6 and 16% in the BT2. These overestimations are still present in the 2016 DOE report for biomass resource assessment, as perennial grasses are still estimated to be grown on cropland with low rainfall levels. The revised total herbaceous biomass predicted still exceeded the target of the RFS2, but the geographical location of biomass production changed.

CHAPTER III

GIS-BASED ALLOCATION OF HERBACEOUS BIOMASS IN BIOREFINERIES AND DEPOTS*

While sufficient biomass has been identified to meet the Renewable Fuel Standard (RFS2) targets by previous studies, availability does not equal access. The objective of this chapter is to quantify the potential accessible and stranded herbaceous biomass from different scenarios of predicted available biomass in both TX and the US. The following Chapter begins with a brief background of biomass logistical issues, a synopsis of the literature, a description of the data and methods used in this analysis, followed by results and discussion.

The location and size of potential biorefineries and depots were determined using the geographic location of suitable lands for biomass, the transportation infrastructure, and published economic constraints for minimum biomass supplied to a facility within a specified neighborhood. A GIS-based heuristic approach was implemented to address the capacitated facility location problem by distributing potential biomass along a county's suitable land. Optional road and rail proximity was included in the algorithm. The methodology described in this chapter determined that the total stranded biomass in TX was 28% of the total available biomass. When including the constraint of the transportation network accessibility (rail and appropriate roads), the total stranded

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biomass increased to 33%. Furthermore, using county centroids as supply points and potential facilities led to an increase of 7% in total biomass captured by all facilities in TX when compared to the raster-based heuristic. In summary, the nationwide accessible biomass was found to be 90% of the available biomass, 78% of which is captured by biorefineries. In total, 77 biorefineries and 171 depots were identified in the US from this analysis, which projects to 184 million Mg year^{-1} delivered to biorefineries and depots, or 65.3 billion liters of advanced biofuels, more than the targeted 60 billion liters of advanced cellulosic biofuel in the RFS2.

Background

Current pioneer biorefineries rely on local supplies of baled biomass with trucks as the primary transport mechanism. In this chapter, such SCh is referred to as the conventional-bale system (CBS). The CBS for biofuels utilizes a decentralized distribution system with low biorefinery capacities and high transportation costs. Based on a studies by Aden et al. (2002) and Riley and Schell (1991), the Department of Energy's (DOE) Office of the Biomass Program (OBP) considered biorefinery capacities of 2,000 DMg day^{-1} to be approximately optimal for a CBS with an 81-km (50-mile) collection radius in a high-yield corn production area. While the weather conditions, water availability, cropping systems, transport load limits and other regulations in some regions in the US are capable of supporting a CBS, conditions in other areas of the US may not. Hence, a portion of the biomass resources in the US may not be accessible to the biomass industry with a CBS. The biomass resources located in these inaccessible areas are referred to in this dissertation as stranded biomass.

Biomass bulk density has a major impact on: storage, harvest and transportation costs; harvest and labor requirements; biorefinery capital cost; energy requirements; material handling; and processing complexity (Hess et al., 2007; Sokhansanj et al., 2002). Truckloads of baled biomass typically are limited by volume rather than weight, resulting in higher delivery costs (transportation and handling) than necessary. To utilize potentially stranded biomass and improve the biomass logistic model, the DOE has proposed an advanced biomass feedstock SCh design that would modify the biomass using a uniform-format feedstock system (UFFS) (Hess et al., 2009). This effort has primarily focused on preprocessing biomass at the point of harvest and/or preprocessing depot into a higher mass bulk density, aerobically stable, standardized, easily transportable, bulk solid or liquid commodity with characteristics similar to grains. Biomass diversity is envisioned to be managed at the preprocessing depot, which allows subsequent supply-system infrastructure to be similar for all biomass resources. Similar studies also propose a network of depots; refer to as “regional biomass preprocessing centers”, as a way to address the transportation issues of this industry (Carolan et al., 2007). The densified material in the UFFS, compared to raw biomass, is improved for longer-term storability, handling, and transport; in addition to being ready for efficient conversion. The UFFS targets dry matter bulk density greater than 0.48 DMg meter^{-3} (30 lb ft^{-3}) after preprocessing (Hess et al., 2009). However, densification requires an unrecoverable energy investment; hence, energy reductions in other portions of the SCh must be obtained to achieve maximum net energy content and minimum total logistic cost. The underlying approach is that by densifying biomass early in the SCh, the transportation cost, energy invested on transportation and loss of biomass due to handling and storing will be reduced. Raw, unprocessed biomass (i.e. as collected from the land) is not in a format suitable for easy handling by high-capacity transportation modes (i.e. rail, barge).

The inclusion of preprocessing depots and the use of high-capacity transportation modes anticipate the expansion of the potential feedstock collection radius of a biorefinery, hence allowing for the development of biorefineries with higher nameplate capacity, reducing feedstock supply risk and introducing more resources into the biomass market. Biorefineries with higher capacities may take advantage of economies of scale and reduce the cost-per-unit of output. A change from the CBS to a UFFS may allow an expansion of feedstock availability for biorefineries and, consequently, offer investors the confidence of a sustainable supply. Consequently, farmers may be able to participate in the added-value process at the depots. The proposed model for the biomass industry has concept similar to the one for co-operative elevators in the grain industry.

Any facility, regardless of size, will source the lowest cost feedstocks, which likely will be a combination of local delivery (bales) and longer distance delivery (higher density biomass). Figure 7 represents the structure of a SCh that would include biorefineries and depots, a combination of the CBS and the UFFS. The larger circles represent the 81-km radius of biomass delivered from a harvesting site to a biorefinery in trucks. The preprocessing depots will provide additional market options for geographically stranded feedstocks that are not within an 81-km biorefinery radius; hence, feedstocks that are not economically feasible to be collected in the CBS (Argo et al., 2013). The smaller circles illustrate the 32-km (20 mile) collection radius of a depot. A densified version of biomass (module transport units, pellets or briquettes) would be delivered from depots to biorefineries. A depot may contribute to the closest biorefinery, but the uniform format would allow each depot to participate in a regional market (represented by dotted lines in Figure 7). Note that even with the inclusion of depots in the system, some biomass might remain stranded.

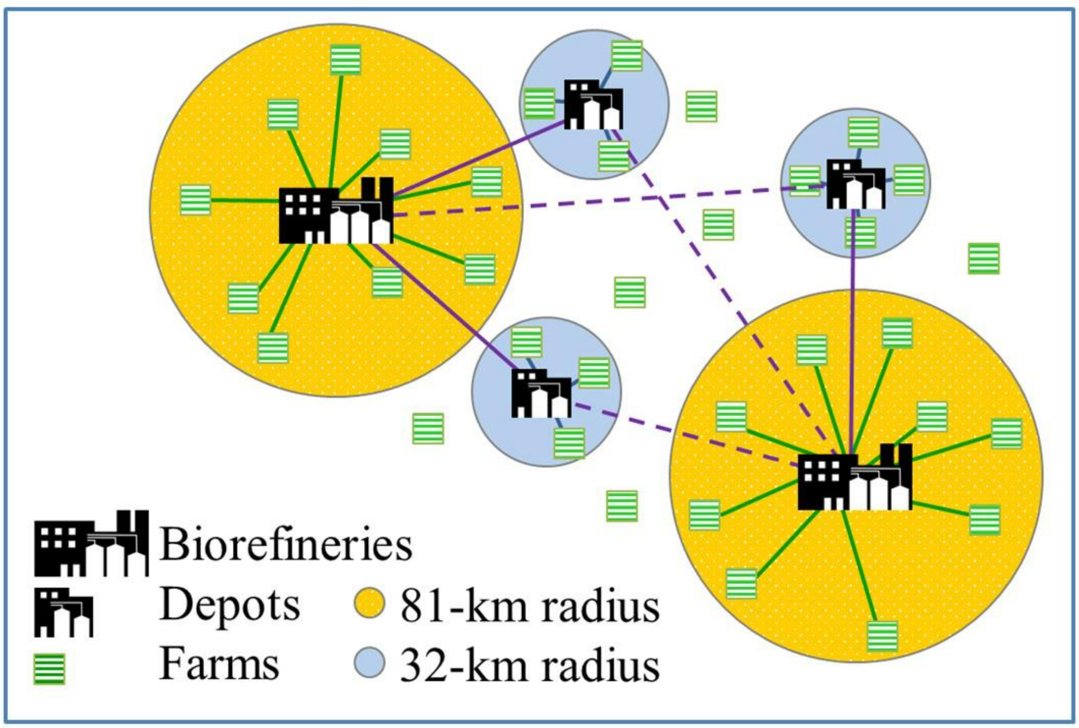


Figure 7 Biomass feedstock supply chain for biorefineries and depots.

In this chapter, our objective was to determine the structure of the likely structure of the biomass feedstock SCh that will develop in the US using herbaceous materials. While sufficient biomass has been identified to meet the RFS2 targets by previous studies (Perlack et al., 2011; Gonzales et al., 2015), availability does not equal access. We evaluated accessibility of herbaceous biomass using different scenarios of predicted biomass given the geographic location of suitable lands for biomass by using appropriate land-use classifications from the 2011 National Land Cover Data (NLCD) (Homer et al., 2015), the transportation infrastructure and constraints based on the economics presented in the literature review for minimum biomass supplied to a facility within a specified neighborhood. The aim of this research was to locate economically viable biorefineries and depots, in addition to quantify potential accessible and stranded biomass. We assumed that technology will be available for a conversion facility capable of handling the different physical and chemical properties of all the potential types of biomass (crop residues and energy crops in baled or high density formats). This study was limited to herbaceous biomass, and all references to biomass production are ignoring biomass from other sources.

Literature review

Reliable inventories of biomass are important for an accurate study of the expansion of the biofuels industry in the US. The DOE published a strategic analysis that estimates the US agriculture and forest resources have the capability to produce at least 907 million DMg (one billion DMT) of biomass annually, in a sustainable manner (Perlack et al., 2011). The Billion Ton Study (BT2) provides a means to predict the development of the biofuels industry. Gonzales et al. (2015) concluded that BT2 estimates of perennial grass were overestimated, by 8% and 87% in the US and TX respectively, for counties with low average precipitation along the 100th Meridian. These assessed geospatial inventories of cellulosic feedstock paved the way to focus on the logistics of agricultural feedstocks for liquid fuel production.

Traditionally, the literature expresses biomass quantities in either dry short US tons (1 short US ton = 0.907 Mg) (Perlack et al., 2011; Jacobson et al., 2014) or in dry metric tons –also referred to as tonnes– (1 metric ton = 1 Mg) (Aden et al., 2002; Lamers et al., 2015). Some research papers are not explicit on what unit (short US tons or metric tons) was used in their studies, which brings some confusion to the readers. In addition, there is a lack of consistency within the literature in the use of DMT as an acronym. Some studies use DMT to express dry matter tonnes (McKendry, 2002; Samora-Cristales et al., 2013) or dry metric tons (Roni et al., 2014). Reports from the Idaho National Laboratory (INL) use DMT to express dry matter tons (Muth et al., 2013; Wright et al., 2012). The lack of unit consistency brings confusion, thus, in this study we used DMg (dry mega grams) as the unit of mass for biomass.

A biorefinery size will have a significant influence on the biofuel production cost. Determining the optimal size for a biorefinery includes recognizing the tradeoffs between economies of scale with larger conversion plants and higher feedstock delivery costs and has been of continuous debate in the literature. Two National Renewable

Energy Laboratory (NREL) studies on biochemical conversion of CS indicated that 2,000 DMg day^{-1} is approximately optimal for a CBS with an 81-km collection radius in a high-yield corn production area (Aden et al., 2002; Riley and Schell, 1991). A different study of the tradeoffs between scale economies and transportation costs through a mathematical model revealed that the estimated net present value of lignocellulosic biomass plants (energy crops, crops and wood residues) is maximized at a capacity of 3,955 DMg day^{-1} (Kaylen et al., 2000). Conversely, Wright and Brown (2007) calculated that the optimal size for a biochemical cellulosic ethanol plant was 4,281,912 DMg. Assuming Wright and Brown estimated a total of 350 working days year^{-1}, the daily plant capacity presented was of 12,232 DMg. A later study reported the optimal plant size to be 3,450 DMg day^{-1} (Leboreiro and Hilaly, 2011) when using a transportation winding factor for feedstock delivery to the plant. They claimed that the big difference in their results compared to Wright and Brown (2007) is because the previous authors used lower hauling costs and ignored storage costs.

Aden et al. (2002) implied that if higher quantities of biomass become available, increasing the plant size from 2,000 to 10,000 DMg day^{-1} decreases the non-feedstock costs by \$0.05 liter^{-1} (\$0.19 gallons^{-1}) or about 25%. But, the increased cost of feedstock to supply the higher-capacity plant, eliminates \$0.034 liter^{-1} of these savings. And, that a plant capacity of 6,000-8,000 DMg day^{-1} will achieve the net savings of \$0.016 liter^{-1} with no additional cost savings realized above that size. Similarly, Hamelinck et al. (2005), analyzed the economics of biorefinery capacities at 2,000, 5,000 and 10,000 DMg day^{-1} and declared that the development of a conversion plant with a capacity higher than 10,000 DMg day^{-1} of lignocellulosic biomass is less evident to be realized. Carolan et al. (2007) concluded that future large biorefineries will have capacities of 4,536-9,072 DMg day^{-1} (5,000-10,000 tons day^{-1}) of biomass to achieve process economies, if not larger. Later studies specified that under a system that includes pre-processing depots, cost advantages can be achieved with larger biorefineries above 5,000 DMg day^{-1} and up to 10,000 DMg day^{-1} (Argo et al., 2013; Lamers et al., 2015; Muth et al., 2014). The Bioenergy Technologies Office's Multi-Year Program Plan of March 2015 has set a cost target of fuel production at \$0.79 liter^{-1} (\$3 gallon^{-1}) of Gasoline Equivalent (GGE) with plant capacities of 2,000 DMg feedstock day^{-1} by 2022 (US DOE, 2015).

Because the idea of a pre-processing depot as an additional echelon to the agricultural feedstock for liquid fuels SCh is relatively new, further research is necessary to estimate an optimal depot size and supply radius. Argo et al. (2013) indicated that the size of a depot is based on the throughput capacity of the grinder, which is the most capital-intensive equipment required at the facility. Lamers et al. (2015) assumed that depots are modular and can be incrementally scaled in a stepwise fashion of 9 Mg hour^{-1} and adopted a maximum depot capacity of 9.07 Mg hour^{-1} in their analysis – note that the capacity of the grinder for the high moisture pelleting process is of 4.5 Mg hour^{-1}. Assuming 350 labor days and 3 shifts per day at the depot, the yearly capacity would be 76,188 Mg year^{-1}.

Locating a facility and determining the nameplate capacity of the facility is the most crucial decision to realize an efficient SCh due to the high investment costs and availability of feedstock (Acharya et al., 2014; Eksioglu et al., 2009). The facility location problem (FLP) in general networks is known as a non-deterministic polynomial-time hard (NP-hard) problem to solve for optimality. The NP-hard classification for decision problems refers to the difficulty to solve the problem. If the algorithm to solve a problem can be translated into one for solving any other NP-problem, a problem is said to be NP-hard. In other words, an NP-hard problem is at least as hard as any NP-problem, but it might be harder (Weisstein, 2015a). An NP-problem permits a nondeterministic solution and the number of steps needed to verify the solution is bounded by some power of the problem's size (Weisstein, 2015b). Consequently, the use of exact solution methods is limited by the size of the problem. Many studies have approached the facility location problem, as well as the capacitated FLP (CFLP) through heuristics such as the local search algorithm, linear-programming rounding, dual-based ascent, lagrangian relaxation, greedy algorithms and greedy augmentation (Charikar et al., 1999a; Charikar et al., 1999b; Erlenkotter, 1978; Guha et al., 1998; Hochbaum, 1982; Jain et al., 2002; Jain and Vazirani, 2001; Kuehn and Hamburger, 1963; Lin and Vitter, 1992; Nauss, 1978; Shmoys et al., 1997). Acharya et al. (2014) presented a decision support system that could be used by managers to solve the SCh problems of capacity and location for a single new or multiple new biorefineries. They addressed four SCh problems: the transportation problem (when location and capacity is known), the capacity allocation and transportation problem (when location is known but the capacity is unknown), the facility location problem (when capacity is known and location is unknown), and the capacitated facility location problem (when capacity and location is unknown). The model was validated with biomass data for Mississippi at the county level obtained from the National Agricultural Statistic Service (NASS). County centroids were identified as potential locations for facilities and biomass supply points.

The rather dispersed distribution of biomass has caused researchers to use spatial analysis to understand the geographic context of bioenergy supplies and analyze the potential for the biofuel industry. A Geographic Information System (GIS) has the capabilities of storing, evaluating, and displaying multiple layers of geospatial data effectively (Noon and Daly, 1996). GIS includes digital maps that are linked to tables of attributes. These attributes can be the amount of SW available or the average annual precipitation in a county. Software packages such as the ESRI ArcMap enabled the analysis and manipulation of geospatial data. Several researchers have used GIS as a decision support system to evaluate the facility location problem for plants fed by agricultural products (Graham et al., 1997; Graham et al., 2000). At the University of Hawaii, researchers linked geospatial data for roads, soil and land-use with forest productivity and economic models to assess the delivery cost of eucalyptus wood to potential conversion facilities on the Hawaiian Islands (Liu et al., 1992; Liu et al., 1993; Phillips et al., 1993). Graham et al. used raster data to locate biorefineries based on the yield and distance to cropland (Graham et al., 2000). Each pixel was a potential biorefinery. A sequential method was used to locate the facilities. Once a facility was located, the croplands that would supply the plant were removed from further consideration to allocate the next facility. Panichelli and Gnansounou applied a least-cost approach to locate various bioenergy facilities (of a fixed capacity) simultaneously based on the significant variability of farmgate prices (2008). Most of the literature assumes that available feedstock for a county is in the centroid (Acharya et al., 2014, Ranney and Cushman, 1979; USDA NASS, 2015) or in county seats (Lamers et al., 2015).

A more spatially accurate means of allocating feedstock would be to utilize datasets such as the NLCD (Perlack et al., 2011) to distribute the biomass within a county on the basis of known land-use. The most recent public inventory of available biomass in the US is the BT2, hence, the BT2 is a better resource to determine the structure and development of the biofuels industry than data from NASS. While previous work has been highly variable in the estimation of an optimum biochemical refinery capacity, a value between 2,000 and 10,000 DMg day^{-1} was most commonly suggested. Thermochemical and pyrolysis facilities may have different optimal sizes. The literature on optimal depot size is limited but it approximates a capacity of 76,188 Mg year^{-1}, as suggested by Lamers et al. (2015).

Datasets and methodology

For this research, we developed the potential structure of the biofuels industry using the best available information in the literature. Initially, we developed a GIS-based heuristic that addresses the capacitated facility location problem based on a maximization of access to biomass resources within a specified neighborhood radius and a minimum of total biomass available to be supplied to a facility. We chose a raster approach as opposed to a network approach given that the former allows for continuous resource surfaces. The algorithm consists of distributing potential biomass along the suitable lands of each county (based on the 2011 NLCD), as opposed to assuming that all the biomass is located in a county centroid.

We used the herbaceous biomass inventories in the baseline scenario presented in the BT2 and the revised inventories under scenarios past100 and all25 from a previous study by Gonzales et al. (2015). In short, the past100 scenario has the same land-use assumptions for perennial grasses as the BT2, but the biomass inventory quantities predicted are different due to improvements to the simulation model used in both studies (Policy Analysis System -POLYSYS) between 2011 and 2015. The all25 scenario used the average annual precipitation county boundaries to restrict all conversion from pastureland and/or cropland to perennial grasses. (The reader is referred to Gonzales et al. (2015) for a deeper understanding of the land-use change assumptions used in the past100 and all25 scenarios.)

Total herbaceous biomass predicted in the BT2 at the \$66.14 Mg^{-1} farmgate price (208 million DMg $year^{-1}$) slightly increased under the past100 scenario (209 million DMg $year^{-1}$) and decreased under the all25 scenario (205 million DMg $year^{-1}$). Even though the inventories were approximately the same in the BT2 and in the study by Gonzales et al, the biomass geographical location changed across the nation. For example, TX herbaceous biomass inventories were 16.4, 6.48 and 4.12 million DMg $year^{-1}$, respectively under the BT2, past100 and all25 scenarios at the \$66.14 Mg^{-1} farmgate price. The values in past100 and all25 scenarios at the \$66.14 Mg^{-1} farmgate price were closer to the BT2 scenario at the \$55.12 Mg^{-1} farmgate price (8.53 million DMg $year^{-1}$). Hence, in this study we used biomass inventory estimates at the \$55.12 Mg^{-1} farmgate price from the BT2 scenario and at the \$66.14 Mg^{-1} farmgate price from the revised inventories by Gonzales et al. (2015).

As per the BT2 assumptions, annual energy crops may be grown on croplands as part of a crop rotation, and perennial grasses may be established on cropland or pastureland (Perlack et al., 2011; Gonzales et al., 2015). Hence, lands classified as cultivated crops in the 2011 NLCD were identified as suitable lands for annual energy crops and crop residues such as barley straw, CS, oats straw, sorghum stubble and WS and a portion of the estimated perennial grasses. Lands classified as grassland/herbaceous and hay/pasture in the 2011 NLCD were identified as suitable lands for the other portion of perennial grasses, estimated to be grown on pastureland in the BT2. For simplicity, we referred to grassland/herbaceous and hay/pasture lands from the NLCD as pastureland, and cultivated crops as cropland. Table 6 illustrates these assumptions.

Table 6 NLCD suitable land classifications for assignment to biomass types.

Cropland	**Pastureland**
- Crop residues (barley, corn, oats, sorghum, wheat) - Annual energy crops -Perennial grass established on cropland	- Perennial grass established on cropland-used as pasture -Perennial grass established on permanent pasture

To allocate the county-based quantities of potential biomass in the NLCD raster data, we first extracted the suitable areas in two different raster files, the cropland and pastureland. The resulting raster files are presented in Figure 8. Note that lands such as wetlands, aquaculture, open water, developed areas, barren and forest were removed from the NLCD layer. In each map, the 100th meridian and the 28th parallel are shown. These were limits to perennial grass production used in the BT2 study. The biomass production attribute value assigned to the pixels representing suitable lands was the total available herbaceous biomass available in a county divided by the total suitable area of that land type (cropland and pastureland) in the county (found using the ArcMap Zonal Statistics tool).

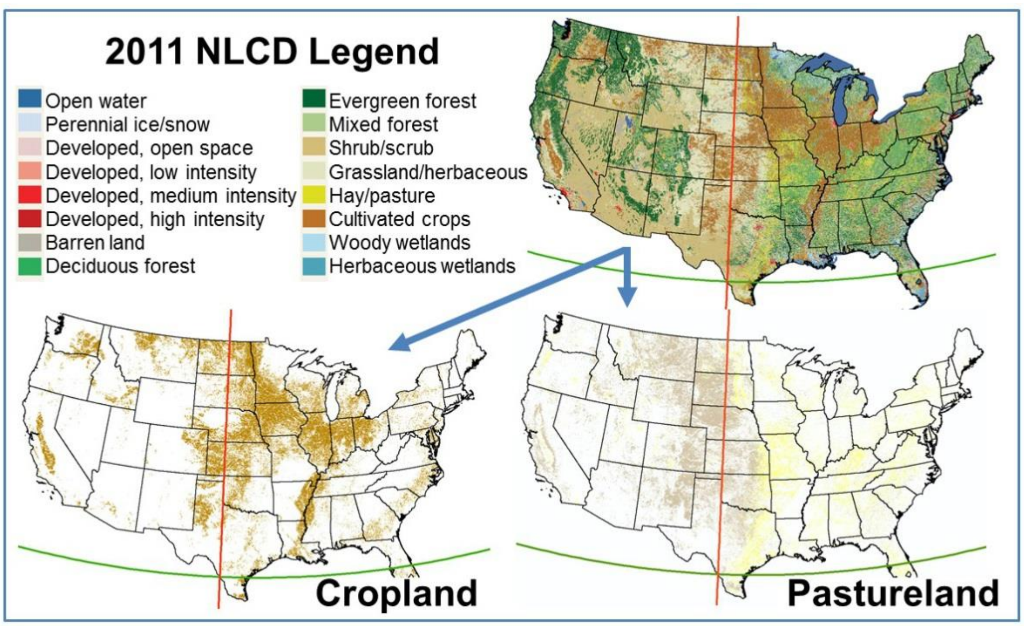


Figure 8 Lands identified as suitable for lignocellulosic biomass from the 2011 NLCD (adapted from Homer et al., 2015).

For example, in scenario all25 the total available herbaceous biomass that is projected to be grown on cropland in Parmer County, TX was estimated at 242,337 DMg (of which 56% is CS, 39% is wheat and 5% is sorghum). Given that the average corn, sorghum and wheat yields in the Parmer County are 913.5, 414.7 and 223.9 DMg km^{-2} (USDA NASS, 2014a) the weighted average herbaceous biomass yield for cropland in Parmer County under this scenario should be 620 DMg km-2. Since the total cropland in Parmer County in the 2011 NLCD raster was 1,645 km2, each 2.59 km2 (1 mile2) pixel that represents the location of cropland in the raster was given a value of 148 DMg in our study to represent the herbaceous biomass yield. In other words, we distributed available biomass evenly throughout suitable areas (cropland in the example) in Parmer County.

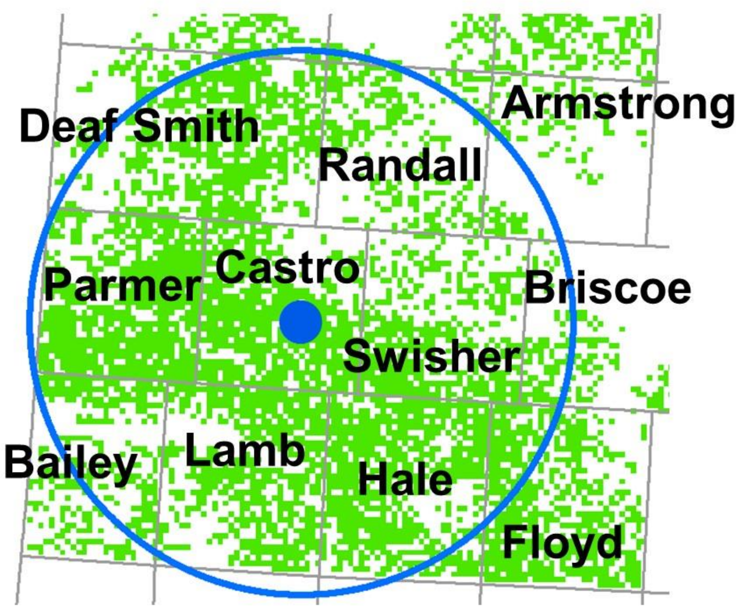
While we acknowledge that our methodology uses a lower-than-actual DMg km^{-2} yield, we believe that the raster approach used here is an improvement over assuming that all the biomass is in the centroid of a county, since the latter implies that the centroid has a very high yield. If we assumed that the centroid is a 2.59 km^2 pixel, then the yield at the centroid of Parmer County would be of 93,566 DMg km^{-2} (242,337 DMg divided by 2.59 km^2) and the yield everywhere else in the county would be zero. Conversely, a different approach would be that for a given county, the yield is the total biomass available over the total area of the county. With this method, every 2.59 km^2 pixel in Parmer County would have a value of 147 DMg km^{-2} (242,337 DMg divided by 2,292 km^2), regardless of whether the location of the pixel is in a suitable land for herbaceous biomass or not. In fact, the county yields for herbaceous biomass found in our study represent a lower bound to estimate the actual yields. The yield values could be refined using the Cropland Data Layer (CDL) (USDA NASS, 2014b), which provides geo-references for specific crops. For this study, we used the NLCD instead of the CDL, because the latter adds additional complexity (time and memory resources).

Map algebra, a tool available in ArcMap, was used to overlap the two different raster files presented in Figure 8 (cropland and pastureland) into a new raster referred to as the biomass raster. In the biomass raster any one pixel in either of the raster files will have a value of zero (other land-use classification), a value of biomass yield from cropland or a value of biomass yield from pastureland. We acquired a rounding error of 1% when converting the data from the database to pixel values in the raster files.

The GIS-based heuristic was run to locate and size the biorefineries and depots that will likely develop in the state of TX by 2022 given the BT2, past100 and all25 scenarios for potential biomass. The contiguous US was evaluated using the results of the all25 scenario. We assumed any biorefinery has the capabilities to handle feedstock in the form of bales (delivered from farms) and densified biomass (delivered from depots). We assumed that a biorefinery needs at least 2,000 DMg day^{-1} (or 700,000 DMg year^{-1} with 350 working days in a year) to operate. Additionally, we constrained the supplied radius for a conversion plant to 81-km radius. Baled biomass will arrive at depots (from farms), where it will be densified. We used 240 DMg day^{-1} as the minimum depot size. Additionally, we constrained the supplied radius for a depot facility to 32-km (20-mile). The supply radius for the depots used aligns with the conceptual UFFS design envisioned by INL (Hess et al., 2009).

The focal statistics tool form ESRI ArcMap was used to evaluate the distribution of the biomass and locate facilities. This tool calculates, for each input pixel, a statistic of the values within a specified neighborhood around it. The input to this tool was the biomass raster, the statistic calculated was a summation with a neighborhood of 81-km. The pixel values on the output raster from the focal statistics tool, referred to as the biomass cumulative raster, was the sum of available biomass within the pixel's 81-km neighborhood. Like the method by R. L. Graham et al. (2000), we considered every pixel in the biomass cumulative raster as a potential biorefinery and used a sequential method to locate the facilities. The pixel in the biomass cumulative raster with the highest value will have the most biomass within its surroundings and hence, it was chosen as the first biorefinery location with a nameplate capacity of that pixel value. Before the next biorefinery location was chosen, the pixel values chosen to supply the biorefinery found are changed to zero in the biomass raster with the extract by circle tool in ArcMap. The new biomass raster was used again as an input to the focal statistics tool to find the next biorefinery. This process was repeated until the pixel with the highest value in the biomass cumulative raster (output of the focal statistics) was less than 2,000 DMg day^{-1}. Assuming a generalized conversion rate of 355 liters DMg^{-1} (85 gallons DMT^{-1}) (US DOE, 2010), the smallest facility will produce 248.5 million liters year^{-1}. The value of pixels that are not assigned to any biorefinery represent stranded biomass.

Figure 9 illustrates how the raster-based heuristic used in this study locates facilities (biorefinery in this case) based on a maximization of available biomass within the supply/market radius. In the figure, the colored pixels/squares represent the herbaceous biomass yields for each county under the all25 scenario. The biorefinery found in the picture was located in Castro County and the market radius of this facility expands to Deaf Smith, Randall, Armstrong, Parmer, Swisher, Briscoe, Bailey, Lamb, Hale and Floyd County. Note that suitable lands in Briscoe County are concentrated in the south and west of the county and about 40% of the county's biomass lies inside Castro's biorefinery market radius. If we were to assume that the biomass in Briscoe County is located at the county centroid (as done in previous studies), none of this biomass would be considered within the Castro's biorefinery market.



County name	Biomass yield (DMg pixel^{-1})
Castro	737
Lamb	475
Parmer	421
Hale	279
Deaf Smith	180
Swisher	173
Randall	161
Bailey	122
Armstrong	61
Floyd	51
Briscoe	28

Figure 9 Representation of yields assigned to each county on suitable lands and the market radius of the biorefinery found in Castro County under the all25 scenario.

To analyze the impact of the proximity to the existing TX transportation network (roads and rails), we extended our study to include a constraint to the algorithm that ensures that a biorefinery may not be located further than 1.62 km from both transportation networks, road and rail. The 1.62 km distance is chosen considering the footprint of the biorefinery facility and the additional storage space for processed and unprocessed feedstock. In addition, this distance was consistent with the size of the NLCD raster used in this study. The road and railroad data layers were obtained from the TX Natural Resources Information System (TNRIS) website (TNRIS, 2013). The roadway raster, as defined by TNRIS, is a comprehensive, routed GIS centerline base map for the state of TX. The roads chosen as suitable for this study are US numbered highways, state highways, farm-to-market roads and all other roads considered to be in the highway system by the TX Department of Transportation, excluding interstate highways. A biorefinery will not be sited on heavily trafficked roads. Thus, the polylines classified as interstate highways in the roadway dataset were removed from the analysis. The Pseudo-code presented in Figure 10 represents the algorithm used to solve the facility location problem. Note that the intersection line in the pseudo-code (in grey text) will only be included in runs with the rail and road transportation proximity as an additional bound to locate facilities. In addition, the variables in the pseudo-code: Biomass(x), BiomassCumulative(x), Road and Rail are raster files that represent the amount of biomass in each pixel, the amount of biomass in the neighborhood of each pixel, and pixels that represent the location of roads and rails, respectively. The biorefinery(x) variable is a set of the biorefineries found.

```
x = 0
Do While cell values <> 0
  x = x + 1
  Focal statistics (Input: Biomass(x) Radius: 81km Output: BiomassCumulative(x))
  Intersection (Input: BiomassCumulative(x) ∩ Road ∩ Rail Output: BiomassCumulative(x))
  If highest cell value in BiomassCumulative(x) ≥ 2,000 DMg Then
    Locate Biorefinery(x)
    Set Cell values 81km radius of Biorefinery(x) = zero (Input: Biomass(x) Output:
Biomass(x+1))
  End If
Loop
```

Figure 10 Pseudo-code for the algorithm to locate biorefineries with a minimum capacity of 2,000 DMg day^{-1} with the option for considering the transportation infrastructure (grey text).

To determine the accessible herbaceous biomass from the total available biomass in TX, we identified potential locations and capacities of biorefineries and depots under different scenarios of predicted biomass (baseline scenario in the BT2, past100 and all25). In addition, we evaluated the incorporation of the transportation network in the heuristic under the all25 scenario for the state of TX. Using the same biomass predictions, we compared our raster-based heuristic with the conventional method of using county centroids as supply points and potential facilities. Finally, we expanded our study to the whole nation using the past100 and all25 scenarios of predicted biomass.

Results and discussion

Table 7 presents the potential biorefineries and depots with a feedstock supply potential of at least 2,000 DMg day^{-1} and 240 DMg day^{-1}, respectively, the total estimated accessible biomass in TX, and the total probable stranded biomass for each of the POLYSYS assumptions. Stranded biomass was calculated by subtracting the biomass that could be accessed by biorefineries and depots from the total potential biomass in the state for a given scenario. We found that 18%, 21% and 28% of the total available biomass was found to be stranded under each of the scenarios studied in this paper, BT2, past100 and all25, respectively. Figure 11 illustrates the geographic location of biorefineries and depots found under each production level assumption as well as the market region that is predicted to supply each facility in this study.

Table 7 Available biomass in TX based on different production level assumptions.

Scenario	County	Capacity (DMg year^{-1})
BT2	Terry biorefinery	1,773,919
	Castro biorefinery	1,550,684
	Hutchinson biorefinery	1,376,335
	15 depots	2,326,296
	Accessible biomass	7,027,234
	Stranded biomass	1,500,370
Past100	Lamb biorefinery	1,795,173
	Moore biorefinery	1,340,766
	Terry biorefinery	754,338
	10 depots	1,264,555
	Accessible biomass	5,154,832
	Stranded biomass	1,329,642
All25	Sherman biorefinery	1,300,233
	Castro biorefinery	1,240,044
	2 depots	417,061
	Accessible biomass	2,957,337
	Stranded biomass	1,151,389

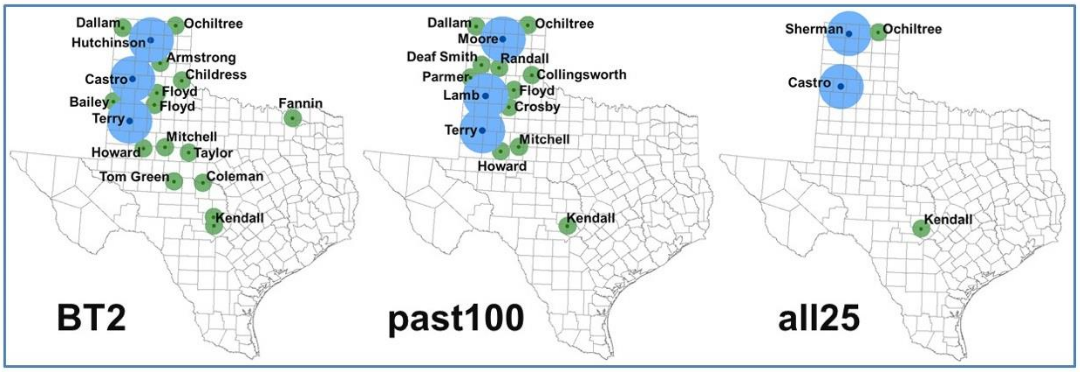


Figure 11 Biorefineries (large blue circles) and depots (small green circles) found under different production level assumptions in Texas.

To analyze the impact of the proximity to the existing TX transportation network, we incorporated the rail and road transportation proximity as a bound to locate facilities under the all25 scenario in TX. The additional constraint, which ensures that a biorefinery may not be located further than 1.62 km from both network (roads and rails), resulted in a decrease of 7% of the total accessible biomass in the system that includes both biorefineries and depots. Consequently, the transportation constraint increases the total stranded biomass under the all25 scenario from 28% to 33% (see Table 8). Note that there was no depot found in Kendall County with the additional transportation bound because Kendall County does not have rail service.

Table 8 Available biomass in TX under the all25 scenario based on proximity to the transportation infrastructure.

Without the transportation network boundary		With the transportation network boundary	
Facility	**Capacity (DMg year^{-1})**	**Facility**	**Capacity (DMg year^{-1})**
Sherman biorefinery	1,300,233	Sherman biorefinery	1,299,744
Castro biorefinery	1,240,044	Castro biorefinery	1,239,366
Ochiltree depot	226,906	Ochiltree depot	220,930
Kendall depot	190,155		
Accessible biomass	**2,957,337**	**Accessible biomass**	**2,760,040**
Stranded biomass	**1,151,389**	**Stranded biomass**	**1,348,686**

To evaluate the effect of the 2,000 DMg day^{-1} capacity assumption for biorefineries under the all25 scenario, we relaxed the capacity constraint to a value of 1,000 DMg day^{-1} and found a biorefinery in Kerr County with a capacity of 1,074 DMg day^{-1}. This biorefinery would be supplied with biomass from Kerr, Bandera, Real, Kimble, Gillespie, Kendall, Bexar, Medina, Edwards, Mason and Uvalde County. Note that in our algorithm, biorefineries are found before depots. Hence, when we adjusted the minimum capacity constraint and found a biorefinery in Kerrr County, a depot was no longer located in Kendall County since the biomass would be destined for Kerr's biorefinery. Figure 12(a) illustrates how the market radius of a biorefinery in Kerr County and a depot in Kendall County would overlap. The rail system does not traverse Kerr County; hence, no biorefinery would be located in Kerr County with a capacity bound of 1,074 DMg day^{-1}. In fact, under the transportation constraint, a third biorefinery would only be found if the capacity bound was lowered to 758 DMg day^{-1}. This third biorefinery would be located in Hemphill County. Note that the 2,000 DMg day^{-1} assumed capacity was based on biochemical conversion processes. Thermochemical facilities may have a different optimal size, which may change the predicted amount of stranded resources and the number and geographical distribution of all facilities.

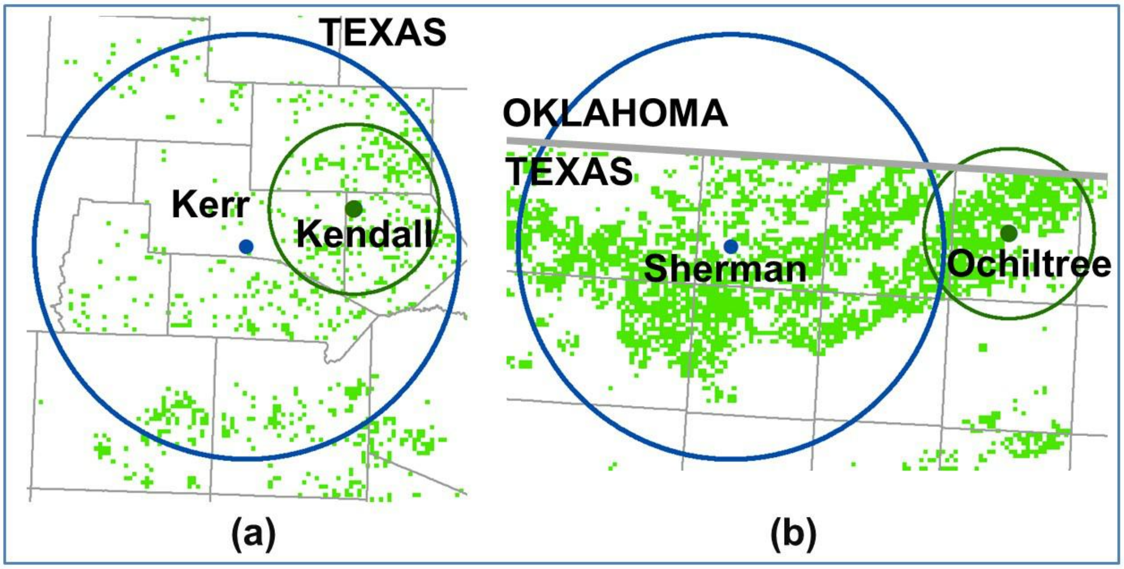


Figure 12 (a) Supply radius overlap of potential biorefinery and depot when relaxing the minimum biorefinery capacity constraint. The heuristic algorithm locates either the biorefinery or the depot. (b) Supply radius intersection between Sherman's biorefinery and Ochiltree's depot.

Our raster-based heuristic did not make any assumptions of where the location of biomass would be other than the suitable lands. However, we recognize that the economic draw of a biorefinery could pull the biomass production into portions of a county closest to that facility. If we were to consider that the entire all25 scenario potential biomass for each county were to be concentrated on suitable land within 81-kms of the Sherman and Castro biorefineries, an increase of 8% and 6% in biomass available would be observed, respectively.

Considering all of the biomass in counties within 32-kms from the Kendall and Ochiltree depots found under the all25 scenario increases the total biomass available in the depots by 45% and 101%, respectively. The high increase in available biomass can be explained with Figure 12(a) and (b). As per Figure 12(a), the counties that would supply the depot in Kendall County have a much higher area than the area of the supply circle. Hence, not all of the biomass in these counties is economically available. Hansford County is both in the neighborhood of the biorefinery located in Sherman County and in the neighborhood of the depot located in Ochiltree County, which explains the high increase of available biomass mentioned before (101%) (see Figure 12(b)). The raster-based heuristic used here ensures that biomass is not double-counted when locating facilities. Sherman County borders the state of Oklahoma, and could potentially collect biomass from beyond TX borders. For the initial analysis, biomass sources were limited to TX. In a study without these border limits, that biorefinery could collect more biomass. This analysis is discussed later in the paper.

To compare our raster-based heuristic with the conventional method of using county centroids as supply points and potential facilities, we set TX county centroids to the values in the all25 biomass inventory and found biorefineries and depots. Similar to the results found from our raster-based heuristic, two biorefineries and two depots were located: one biorefinery each in Sherman and Castro Counties, and one depot each in Ochiltree and Kendall Counties. Using the centroids as supply points and potential facilities led to an increase of 7% in total biomass captured by all facilities in TX when compared to our raster-based heuristic. An overestimation of total biomass captured would mislead investors in their risk analysis for a sustainable supply. Due to time constraints, we did not apply the county centroid approach nationwide; hence, we were not able to quantify the difference between the county centroid approach and the raster approach on a nationwide basis. But, we expect that in regions with more uniformly distributed biomass, the gap between approaches will be lower than 7%.

The GIS-based heuristic to address the capacitated facility location problem presented here was expanded to evaluate the national feedstock SCh. We used the inventories of the past100 and all25 scenarios to evaluate the structure of the likely biomass feedstock SCh that will develop nationwide. Under the all25 scenario, we found a total of 77 biorefineries with capacities greater than 2,000 Mg day^{-1} and 171 depots with capacities greater than 240 Mg day^{-1} (Figure 13). Of the total available biomass, 78% could be accessed by biorefineries and an additional 12% by depots, leaving 10% as stranded biomass. A total of 161 million Mg year^{-1} of feedstock delivered to biorefineries around the US and 22.7 million Mg year^{-1} of feedstock delivered to depots. This translates to 65.3 billion liters of advanced biofuels, more than the targeted 60 billion liters of advanced cellulosic biofuel in the RFS2.

Figure 13 maps all the biorefineries and depots found in the US. The five largest biorefineries were found in: McLean County, IL (8,738,123 DMg year^{-1}), Lee County, IL (6,902,892 DMg year^{-1}), White County, IN (5,771,593 DMg year^{-1}), Macoupin, IL (5,172,079 DMg year^{-1}) and Hamilton, IA (4,983,288 DMg year^{-1}). The nationwide analysis, when compared to the analysis solely within TX, lead to a 25% increase in biomass accessed by biorefineries and depots located in TX (3,355,552 DMg year^{-1} –

Table 9– as opposed to 2,957,337 accessible biomass–Table 8). This discrepancy is explained by the ability of the raster-based heuristic to locate facilities regardless of political boundaries. When considering the biomass available nationwide, the location of the biorefinery found in Sherman County, TX shifted 28 km northeast to capture biomass in the state of Oklahoma. As a result, available biomass in Dallam County was removed from the Sherman County market radius. In combination with nearby counties, there was sufficient biomass to locate a third TX depot in Dallam County (Figure 13).

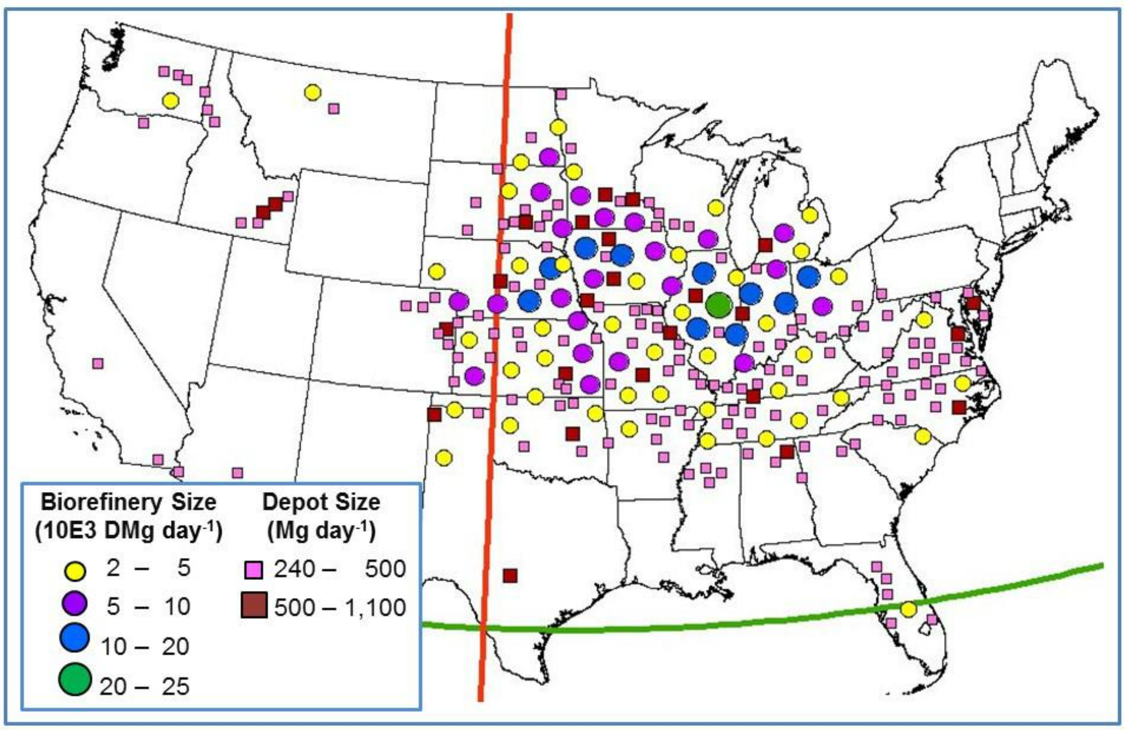


Figure 13 Map of biorefineries and depots found in the US using the all25 biomass inventory.

Because the constraint differences between the past100 and all25 scenarios are mainly in the states along the 100th Meridian (Texas, Oklahoma, Kansas, Nebraska, South Dakota and North Dakota), we also applied the raster-based heuristic to the past100 scenario to identify accessible biomass (see Table 9). TX was the state most impacted by the difference by the land-use change assumptions between the two scenarios, with a decrease of 39% in total accessible biomass. The small increase observed in total accessible biomass in Nebraska is explained by a depot found in Rawlins County, Kansas with the past100 inventory, but under all25 estimates, the depot shifts to Hitchcock County, Nebraska.

Table 9 Total accessible biomass for the US and states along the 100th meridian.

Geographic scope	Accessible biomass (DMg year^{-1})		Percent change from past100
	Past100	All25	
US	191,056,588	183,999,460	-4%
Texas	5,473,744	3,355,552	-39%
Oklahoma	4,361,368	4,180,452	-4%
Kansas	16,725,332	15,834,480	-5%
Nebraska	18,582,173	18,628,928	0.3%
North Dakota	7,949,884	7,879,250	-1%
South Dakota	4,025,649	4,025,649	No change

A raster approach, as opposed to a network approach, allows for the analysis of continuous resource surfaces. Hence, the approach used this study eliminated county and state boundaries for biomass resource delivery to a conversion or preprocessing facility. When focal statistics were applied, the pixel values were changed, based on the neighboring values, regardless of political boundaries. That was in contrast to the previous studies that constrained the collection radius for a location to just one county or state. Our approach also took into consideration geographical data for the existing road and rail systems. Furthermore, the sequence of locating facilities with the algorithm will most likely resemble the progression of the cellulosic industry development (i.e. locations with the greatest available biomass will have facilities first).

The total stranded biomass in TX was between 16-28% of the total available biomass, depending on the biomass inventory and/or political boundary considered. The addition of the transportation network accessibility (rail and appropriate roads) in the biofuels industry increased the total stranded biomass in TX from 28% to 33% under the all25 scenario. An increase of 25% in total accessible biomass for TX based facilities was observed when the counties from adjacent states were allowed to provide feedstocks as opposed to limiting the analysis to only TX counties. We estimated that total nationwide accessible biomass was 90% of the available biomass when delivered to biorefineries (77 locations accepting78% of biomass) and depots (171 depots accepting 12% of biomass).

Conclusions

While addressing the capacitated facility location problem for biorefineries and depots using the raster approach presented here take additional computing time and effort compared to assuming locations at county centroids, several advantages were found to justify the use of the geographic data provided by the National Land Cover Data. Assigning all biomass to county centroids as opposed to distributing that biomass across appropriate land areas results in an estimated increase of 7% of total biomass estimated to be captured by all facilities in TX, an overestimation that would affect sustainability policies and planning. The discrepancy in biomass estimations between the two different approaches may be a result of the average county size in TX (2,699 km^2) in combination with the assumed biorefinery and depot market radius (20,612 and 6,217 km^2) and/or the heterogeneous geography of the state.

Future research could include analyzing different alternative market radius constraints or varying minimum economic sizes for biorefineries and depots, and evaluating the impact on facility location when replacing the total biomass per county with total energy content per county. Additionally, an interesting approach would be to use the same algorithm to evaluate a system that will deliver all available biomass from farms to depots and optimize the location of biorefineries with mixed-integer programming while considering each depot as a supplier to a potential biorefinery.

CHAPTER IV

ANALYSIS OF A MODULE-BASED BIOMASS COLLECTION SYSTEM

Background

Following the droughts of 2011 and 2012 in the US, the need to improve the collection and conservation ability to storage herbaceous biomass became a great concern to the animal feed industry. In most cases, droughts resulted in longer truck hauls of baled material to meet the animal feed demands. Delivery prices for stricken areas are higher than necessary because typical bale densities result in truck capacities being limited by volume rather than weight. Similar concerns arise for the biofuels industry. Biomass logistics account for a major portion of the total feedstock supply cost and energy consumption, and therefore improvements in the systems can substantially improve the feedstock cost-competitiveness (Miao et al., 2012). Biomass bulk density has a major impact on storage and transportation costs; harvest and transportation labor requirements; and biorefinery capital cost, energy requirements and material handling and processing complexity (Hess et al., 2007; Sokhansanj and Turhollow, 2002). But, since densification requires an unrecoverable energy investment, unavoidably reducing the net energy gain, densification should be no greater than needed to achieve minimum total logistics cost. Desirable characteristics of a low-cost biomass logistics system would include independence of strict moisture and weather conditions; minimal non-value-added operations; weight-limited transport that maximizes dry matter shipped per load; rapid loading and unloading with little labor input; and distributed, highly-flexible, strategically located storage. Ravula et al. (2008) described the similarities between the cotton and the biomass logistic system and suggested that the biomass industry might be able to apply operational strategies from the cotton industry. An and Searcy (2012) demonstrated the successful transport of individual, plastic wrapped modules using the tilting chain bed truck used with cotton modules. Cook and Shinners (2011) studied different logistic systems for CS and determined that high-density silage bags, currently used for forage, were 25% less than for dry bales. The objective of this chapter was to study an unexplored alternative to biomass densification that consists of integrating mechanisms and processes proven successful in forage and cotton industries.

Literature review

Most biomass feedstock systems focus almost exclusively on dry bales. However, bale systems have not reached critical adoption due to logistic and economic limitations as presented by Shinners et al. (2003); Sokhansanj et al. (2006); Brechbill et al., (2011); Wright et al. (2006); Cundiff and Grisso (2008); Petrolia (2008); and Cook and Shinners (2011). They considered baling and on-farm distributed storage, followed by year round transport to the processor. In these studies, the cost of delivered feedstock was estimated between \$50 and \$116 DMg^{-1} (\$45 and \$105 DMT^{-1}) for transport distances between 32 and 161 km (20 and 100 miles). However, many of these studies did not include bale decomposition or biomass grinding at the biorefinery, operations that are expensive and time-consuming. In a more comprehensive review of CS, conversion ready costs for bales were \$138 DMg^{-1} (\$125 DMT^{-1}) (Cook and Shinners, 2011). Storage losses, bale handling and in-refinery bale processing made up more than 30% of that cost.

Many of the biomass crops need an extensive period of field drying to achieve storage stable moisture in bales. Long drying times increase risks of weather related delays and losses. Crops residues like CS harvested from windrows often become contaminated with soil. Bales can be stored indoors or covered, but then storage costs are high due to the bale volumes and hence, storage area required. Alternatively, bales can be stored outdoors uncovered, but at the expense of being subject to biological degradation and have very non-uniform composition at removal from storage. Moisture content (MC) has negligible effect on round and square bale transport cost when the load is volume-limited. At current densities of common biomass bales, moisture does not affect transport costs until roughly 35%. At high moistures, bales have to be removed from the load to prevent exceeding load limits, which may reduce the load weight considerably depending on bale size (Shinners et al., 2007; 2010).

Previous economic analyses comparing bale versus chopped biomass systems often considered chopped biomass transported only in loose-bulk form. Loose chopped bulk density of common biomass feedstocks has been reported to range between 40 to 128 kg m^{-3} (2.5 to 8 lb DM ft^{-3}) (Chevanan et al., 2010; Sokhansanj et al., 2010). Brownell, D. K., et al. (2012) studied forage harvesting systems and reported bulk densities that range from 101 to 160 kg DM m^{-3} (6.3 to 10 lb ft^{-3}). These values are clearly insufficient to meet the economic goal of weight-limited transport. For instance, transport cost of loose-bulk CS was 64% greater than stover in large square bales (Sokhansanj et al., 2009). However, because chopped material does not need to be ground like bales, biorefinery processing costs were reduced by 12% and therefore the overall cost of loose-bulk material was only 10% greater than bales. In a similar study where shorter transport distances were considered, the cost of delivered loose-bulk biomass was actually 10% less than baled reed canarygrass (Lindh et al., 2008). Cook and Shinners (2011) compared traditional baled CS to a chopped system using high-density modules and determined that delivered and conversion ready cost of the chopped, modularized material was 23% less than baled material. These economic studies show that if storage and transport density of chopped material could be improved to approach or exceed that of dry bales, there would be considerable cost advantages compared to the traditional dry bale systems.

US DOE funded five high-tonnage logistic projects to investigate improved storage and transport density for cellulosic ethanol production (2012b). The goal was to validate "sustainable feedstock supply and logistics cost of \$88.2 DMg^{-1} (\$80 DMT^{-1}) at the conversion reactor throat (including grower payment and logistic cost)" (US DOE, 2014a). Three of those addressed herbaceous crops and, of those three, two (AGCO and FDC Enterprises) are based on single-pass high density square bales with self-propelled baling technologies. The FDCE study was evaluated at densities of 177 kg m^{-3} (11 lb ft^{-3}) and 225 kg m^{-3} (14 lb ft^{-3}), which resulted in logistics costs of \$54.84 and \$51.79 DMg^{-1}, respectively. The AGCO study was evaluated at densities of 177 kg m^{-3} (11 lb ft^{-3}) and 201 kg m^{-3} (12.5 lb ft^{-3}), which resulted in logistics costs of \$54.48 and \$51.79

DMg^{-1}, respectively. When combining the least-cost technologies demonstrated by AGCO and FDCE (AGCO's single-pass harvest system with FDCE's equipment for collection and transport) the logistics cost reduced to \$45.93 and to \$34.69 DMg^{-1} only if the highest bale-density achieved during field trials (225 kg m^{-3}) can be consistently achieved (US DOE, 2014b). The project by TennEra, LLC (formerly Genera Inc.) focused on chopping field-dried SW with a mower conditioner, blowing SW into a dump for delivery to depots (16 km) and compacting SW for delivery to biorefineries (38 km). The estimated logistic cost by TennEra was \$60.8 DMg^{-1}. With an additional grower payment \$ 29.77 DMg^{-1}, cost estimates presented by AGCO, FDCE and TennEra met the goal of \$88.2 DMg^{-1} (TennEra's estimations were over by only 3%). These approaches are in addition to the uniform format (pelleted) feedstock pursued primarily by the Idaho National Laboratory.

Tube silos are widely used for livestock feed storage, given the flexibility of storage location and anaerobic environment it provides. The dry density of common biomass crops stored in tube silos ranged from 120 to 176 kg m^{-3} (7.5 to 11 lb. DM ft^{-3}) (Shinners et al., 2011; Williams et al., 2012). Muck and Holmes (2001) reported that tube silo density of alfalfa, a crop with similar physical properties to many grass biomass crops, ranged from 205 to 232 kg m^{-3} (12.8 to 14.5 lb. DM ft^{-3}). Significantly, density increased with DM content, so achieving desired density with high DM biomass feedstocks appears feasible. At the lowest tube silo density and 20% moisture, weight-limited transport would not be achieved, but at the highest density and 30% moisture, the transport goal is feasible. In a tube silo, moist material is preserved by low-level fermentation or pretreatment and dry material remains inert. This system has shown to be successful at conserving feedstock value across a variety of biomass crops stored at 55 to 80% DM.

Our research goal was to analyze a SCh system that collects biomass with a wide range of crop moistures; anaerobically stores biomass in tube silos; creates transport units of varied length (length is chosen to optimize shipping volume and weight limits based on the moisture and density achieved in the tube silo) as needed by the industry and loaded on a truck; maintains the as-stored density throughout transport to the point of consumption; and thus minimizes transport costs and eliminates the need of re-densification. The system was defined as the BioMass Optimized Delivery System (BioMODS). Compared to traditional dry bale systems, the BioMODS system does not require extensive field drying to achieve safe long –term storage; eliminates many parasitic field operations, has less soil-contamination; and produces the needed size-reduction at the time of harvest, and may minimize or eliminate downstream processes like bale decomposition and grinding.

To represent the behavior of a system one can develop an optimization model to arrive at solutions that minimize costs. But, optimization models may require considerable running time and data. Alternatively, metaheuristics or mathematical programming (MP) can be used to simplify a system; but, this simplification occurs at the expense of detail in the model, which may jeopardize the value and representation of the system. Discrete event simulation models allow us to represent a complex system with numerous interacting elements that follow a stochastic behavior within a reasonable computational burden. The model presented is an extension of the IBSAL (Integrated Biomass Supply Analysis and Logistics) model developed by Sokhansanj et al. (2006) at ORNL. IBSAL is a collection of discrete event simulation elements programmed in ExtendSim, a simulation package (Image That, Inc., 2013). Details of the IBSAL model can be found in the report by Sokhansanj et al. (2008a).

The IBSAL framework has been extensively used by researchers to evaluate the biomass SCh. Kumar and Sokhansanj (2007) determined that the cost of delivered bales was \$44-\$47 DMT^{-1} (round and square); \$37 DMT^{-1} for delivered loafs (size 2.4 m × 3.6 m × 6 m); \$40 DMT^{-1} for chopped biomass; and \$48 DMT^{-1} for ensiled chops. Sokhansanj et al. (2008b) investigated five scenarios to harvesting straw: large square bales, round bales, large compacted stacks –or loafs, dried chops, and wet chops. He found that there was no significant difference between round and square bales, loafing was the cheapest option at \$17.08 DMT^{-1}, but required more energy input than baling and are not protected from weather. Stephen et al. (2010) evaluated the impact of residue yield on the biomass delivered cost. Sokhansanj et al. (2010) proposed a SCh for heat and power for a dry mill ethanol plant based on corn stover (CS) as feedstock. An and Searcy (2012) extended the capabilities of IBSAL to minimize logistic costs by maximizing highway load and minimizing load/unload times using sorghum modules. The cost of biomass sorghum delivered in the studied transport-modules by Searcy et al. (2012) was 39 to 51% less than a dry bale system. Searcy et al. (2012) also extended the IBSAL simulation software to provide the ability to utilize daily weather data from the National Climatic Data Center provided by the US National Oceanic and Atmospheric

Administration (NOAA) (in addition to the Typical Meteorological Year (TMY) data used in the original IBSAL version).

IBSAL-MC (Multiple Crops) (Ebadian, 2013) is a modified model of IBSAL (Sokhansanj, 2006) that, as opposed to IBSAL, can simulate more than one biomass type in each simulation run. All of the differences between IBSAL and IBSAL-MC are depicted in Ebadian's dissertation (2013). IBSAL-MC does not have the capability to simulate the BioMODS system. By using the IBSAL and IBSAL-MC models as a baseline, IBSAL-BioMODS was developed via ExtendSim Suite version 9.2. Differences between the IBSAL-BioMODS and IBSAL-MC are outlined later in the manuscript.

The BioMODS system

The simulated model was simplified into ten major operations and represented as simulation blocks in the IBSAL-BioMODS model: 1) field setup, 2) mow and windrow, 3) forage harvest and box truck load, 4) box truck delivery to storage, 5) box truck unload and bag-forming, 6) bag seal, 7) bag storage, 8) scale, cut and load module to flatbed truck, 9) flatbed delivery to facility, 10) module unload at facility (Figure 14). The IBSAL-BioMODS is capable of simulating the collection of three different types of biomass (WS, SW and CS) in the same simulation, much like IBSAL-MC. But, unlike IBSAL-MC, the user does not need to input a database of fields to supply a biorefinery. Fields are created based on the total demand at the biorefinery, field size and yields input by the user. The simulation items pass through various simulation elements, in which several attributes are updated (mass, area, MC, density, etc.) within the simulation items and/or in databases; and resources used are calculated (cost, energy required, CO2 emissions). The cost, energy requirements and CO2 emissions in IBSAL-BioMODS were calculated in the same manner as in previous IBSAL models (Turhollow et al., 2009). For every simulation run, two types of costs were calculated and reported for every logistic process: the custom rates (when leasing machines) and the cost of ownership. The variable cost to lease machines, which is based on machine usage, is typically higher than the variable cost of owning the machines. But, the ownership cost entails an additional annual fixed cost per machine. The simulation time in IBSAL-BioMODS represents 365 days that start in July and end in June.

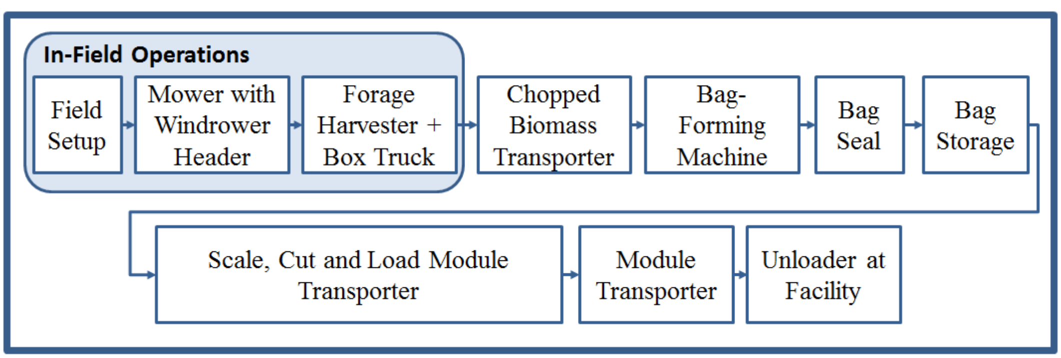


Figure 14 Supply Chain of the BioMODS System.

The fields are first mowed and windrowed (using a mower with a windrower header). The chopped biomass is then collected by a self-propelled forage harvester that blows biomass into a box truck that operates along the harvester. The mowing and harvesting logistic processes are bound by daily weather conditions, MC of the material and operating hours. Inappropriate weather conditions causes delays on these processes. The harvester is also bounded by the biomass MC (MC), which represents the logic for field-drying operations. Harvesting operations are delayed if MC is not below a user-defined critical value, but delays due to inadequate MC are bounded only to a user-defined maximum days in queue. In addition, a field may only wait for a maximum number of days (usually longer than days in queue due to inadequate MC) to be harvested after it has being mowed. Fields that wait too long are considered lost due to decomposition. These delays are further explained later in the manuscript. The materials chopped by forage harvesters are assumed to be used in a conversion plant without any additional size-reduction process. In IBSAL-MC, when bales were ready at the field, a decision was made to whether the bales were delivered straight to the conversion facility or a storage facility. In IBSAL-BioMODS, once a box truck load has reached either the volume or weight legal capacities, it delivers biomass to a storage facility, where it dumps the biomass into a bag-former machine. The bag-former creates compaction by forcing material into a fixed tunnel until a target density is reached. At that point, the forces compacting material into the tunnel are great enough to overcome the system used to restrain bagger movement (wheel or cable brakes or internal anchors), causing the bagger to move forward and create room for additional material. As the material exits the tunnel, it expands slightly, stretching the tube and insuring good anaerobic conditions at the tube/crop interface. The biomass is stored anaerobically at high densities in plastic tube silos and the mass of material placed in the tube is quantified at formation. A tube silo is supplied by multiple box trucks of chopped biomass. Once a tube silo, or bag, is full, it is manually sealed by a sealing operator. In a tube silo, moist material will be preserved by low-level fermentation or pretreatment and dry material will remain inert. Stored biomass is collected daily as demanded by the conversion facility. Tube silos are segmented into transport modules of different lengths. The length is determined by the legal gross weight and volume allowances for a flatbed truck and the moisture content and density of the tube silo. The complete module loading cycle includes cutting, weighting and loading the transport module into a flatbed truck. The flatbed truck delivers biomass to the conversion facility, where biomass is unloaded.

The SCh simulation is a push/pull system, where the items that represent biomass fields are pushed through the system as soon as the harvesting period (HP) starts until the items represent sealed silo bags located in storage facilities. Biomass in fields is collected only during the HP, as the farmers will need to prepare the land for the next cropping season. Once the biomass has being collected, the SCh becomes a pull system, where biomass is moved downstream only as fast as the daily demand at the conversion facility. All attributes have initial values that can be edited by the user. Simulation items throughout the model represent biomass in different formats (field-standing biomass, fractions of a field, chopped biomass in box trucks, plastic tube silos, etc). Each time simulation items are accumulated into a single item (such as several box truck loads into a tube silo bag) or an item is broken down into several items (such as a tube silo into transport modules), all the attributes (mass, area, MC, density, etc.) are updated. These values are calculated or retrieved from the input database.

The user is able to change any values in the input database and the model main interface. The user interface values include: cost parameters (nutrient replacement cost, land charge for storage, bag cost, bag seal cost, interest rate); site parameters (mean and , standard deviation for the area of fields, maximum supply radius for storage, maximum storage size, clearance between bags in a row, clearance between bags in a column, maximum supply radius for biorefinery); resource quantities (number of mowers, forage harvester, bag forming machines, bag/cutter loaders, box trucks, flat-bed trucks and unloaders available); daily working hours for all operations; and biomass parameters such as yields, demand, critical MC for field operations and maximum days in queue to wait for appropriate MC. Note that parameter units throughout the model vary between metric and imperial units and appropriate conversions are embedded throughout the code of the model.

Simulation blocks in the BioMODS system

Field setup

The flow chart presented in Figure 15 is a simplification of the first simulation block. Three items are created that represent each of the biomass types simulated: WS, SW and CS. Each item has mass, yield, and first and last day of harvest attributes. If input was zero for demand or yield for a biomass type, the item exits the system. Else, the item is held in the system until the current day (iDay) is the first day of the HP. Each item is further divided into items representing zones. The number of zones is the division of the biorefinery supply radius by double the supply radius of storage locations. For example, if the biorefinery supply radius was 80 km and the storage supply radius was 8 km, supply area is divided into 5 zones, hence, 15 simulation items (Figure 16). The flexibility of the number of zones and their area are based on user inputs are an extension to the IBSAL-MC. The system does not assign geographic locations for storage facilities, but assumes a uniform distribution within the zone. The inner zone, or closest to the conversion facility has a circle shape with a radius double the supply radius of the storage locations. The second zone, when applicable, has a donut shape calculated by double the radius of the most inner zone minus the area of the most inner zone. In the same way, the third inner zone is calculated by subtracting the second zone to the area of a circle with a radius triple the supply radius of the most inner zone. The following zones would be calculated in a similar manner. The total biomass and biomass area in each zone is proportionate to the total biomass demanded by the facility and the calculated sizes of each zone. Items are further divided to represent fields that supply the biorefinery and continue through the system into the next simulation block. The number of fields for each zone is determined dividing area of each zone by the field size. The fields have random sizes with a normal distribution.

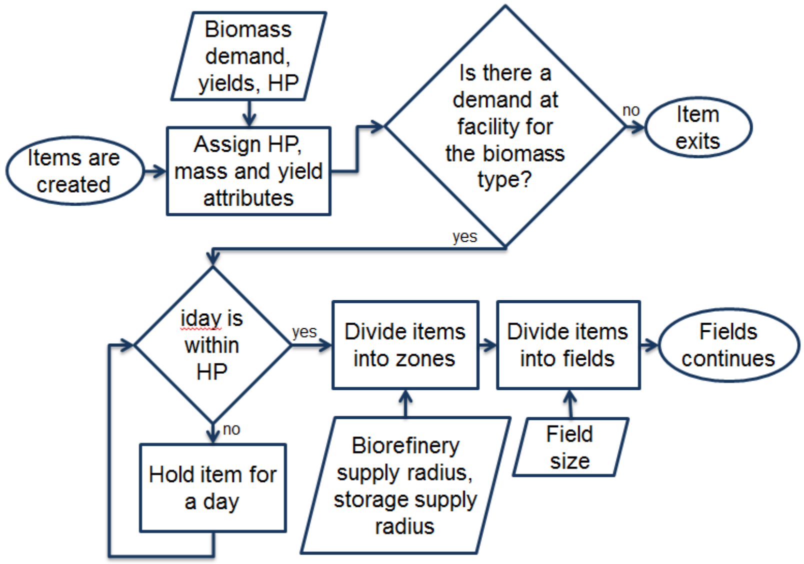


Figure 15 Field setup simulation block.

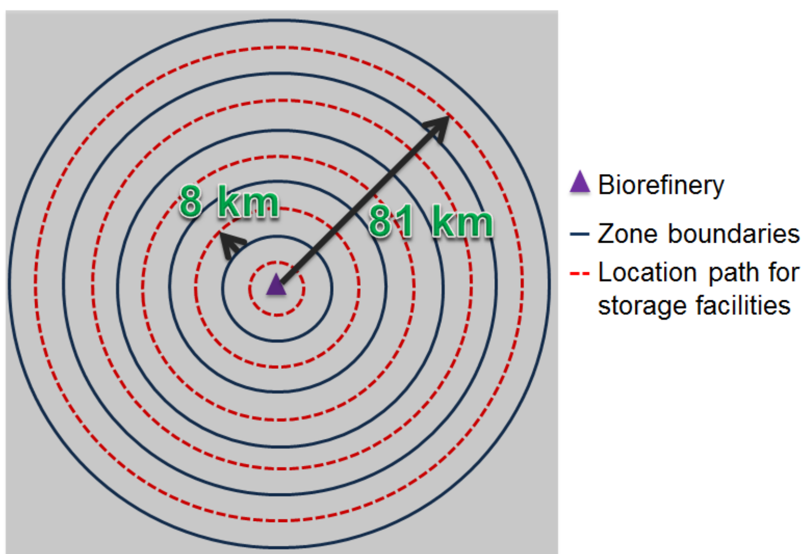


Figure 16 Graphic representation of the supply radius for the biorefinery and the location path for storage facilities.

Mow and windrow

Incoming items to this simulation block (Figure 17) represent fields that are broken down based on the mower capacity per hour (or smaller) and paired up with an available mower that has a windrower header. These fractions of fields may only be mowed if weather conditions are appropriate, a machine is available and only during the HP and in-field operations working hours. Simulation items going out of the simulation block represent biomass items that are mowed and windrowed.

Items are further divided to represent fractions of a field that can be mowed in an hour (or less). Similar to previous IBSAL models, the harvester capacity is calculated in area per hour by multiplying the width of the mower by the average field speed, machine efficiency and field efficiency. The number of items per field is calculated dividing the area mowed over the mower capacity. Note that, when applicable, the remainder of the division will be a fraction of a field than can be mowed in less than an hour. These items are held in queue until all apply: weather conditions are appropriate, running time is within working hours and there is a mower available. If the time items are out of queue is outside the HP, the field fractions exit the system and are considered lost due to lack of time. Else, items are mowed and windrowed after machine repairs, when applicable (machine failures are further explained later in the manuscript). The MC and the mass of the item are updated based on the daily weather and the matter lost due to machine use. After an item has being mowed, it is separated from the mower (operation that makes the machine available again) and continues through the system and out of the simulation block representing biomass that is mowed and windrowed.

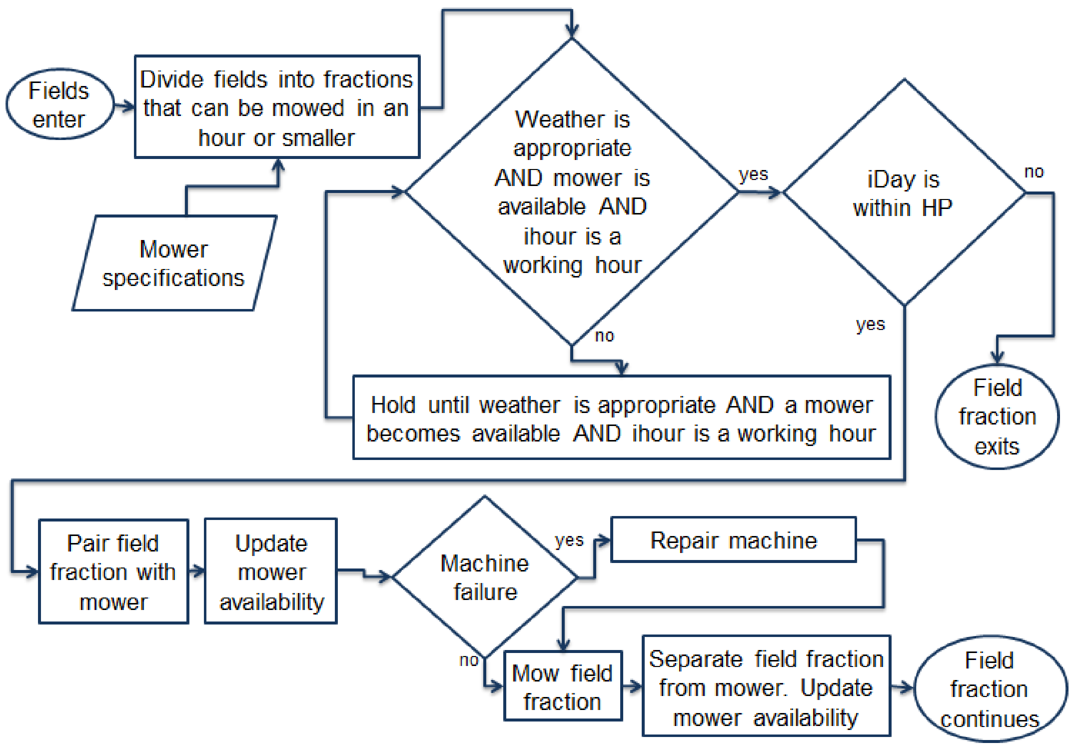


Figure 17 Mow and windrow simulation block.

Forage harvest and box truck load

The flow chart presented in Figure 18 is a simplification of the third simulation block. In this block items are divided into mass quantities that maximize legal box truck load (based on wet mass) or the volume capacity of a box truck (based on dry mass). Biomass is left in field if item represents less than 0.907 Mg (1 ton) of biomass. The weight limit is determined by the volume capacity based on the density of the chopped material (user input in lb ft^{-3}) and is compared to the legal load allowed (user input). The minimum between the weight limit by volume and the legal load allowed is the bound to disaggregate items. Note that the MC of the biomass determines whether the bound will be the box truck volume or the legal load. For example, given that the weight bound is 14.5 wet Mg (16 wet tons) and the volume bound is 36 m^3 (1,280 ft^3) with a chopped density of 0.128 DMg m^{-3} (0.004 DM tons ft^{-3}), the volume bound is 4.6 DMg (5.12 DMT). But, the legal load bound depends on the MC. When MC is 0.7, weight is the bound used, since the volume capacity translates into 15.4 wet Mg (17 wet tons), which is higher than the legal load. But, when MC is 0.3, volume is the bound since the volume capacity translates into 7.3 wet tons. As biomass is harvested, it is blown into a box truck. Biomass loss is expected during pick up at harvester and during blowing from the harvester to the box truck. Rotz (1995) equations were used to calculate biomass lost during forage harvest. Pick up loss = 0.013383/ (MC (w.b.) * biomass density), where weight is in DM tons and density is in tons per acre (density is based on the windrow width formed by the mower). Spout loss = 0.002*(MC $(w.b.)^{-4}$). Biomass may only be harvested if a harvester and a box truck are available, current weather conditions are appropriate, current time (iHour) is within the in-field operations working hours and if MC (wet basis) is below a user-defined critical value and the item has not waited in queue longer than a maximum amount of days since being mowed. If all conditions are appropriate and machines are available, but the MC is above the critical value, an item may be harvested if the maximum days in queue (user-input value) have being reached.

Items are paired up with available harvester and box truck and held in system for processing time that represents harvesting rate, box truck loading and delays due to machine failure. Attributes of items that are matched with the two machines are updated to represent biomass loss at pick up and when biomass is blown into box truck. Items representing full box trucks of chopped biomass are separated from the harvester (operation that makes the machine available again) and continues through the system and out of the simulation block.

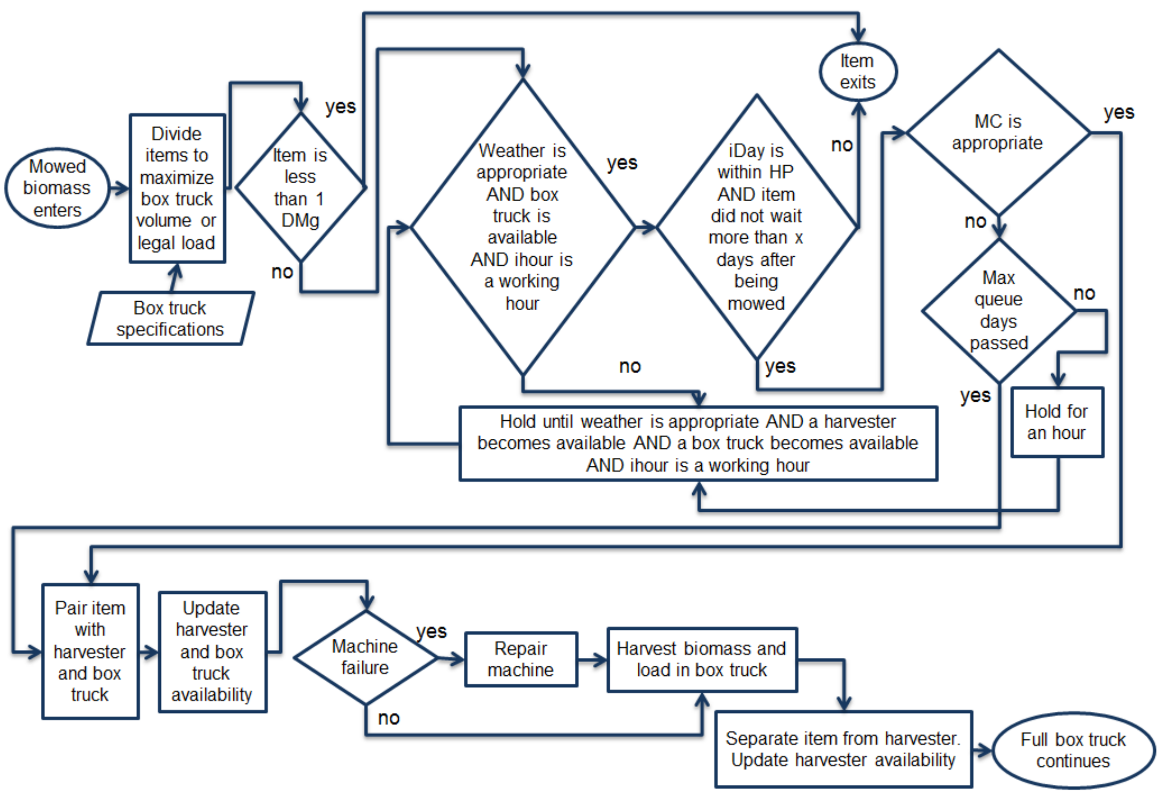


Figure 18 Forage harvest and box truck load simulation block.

Box truck delivery to storage

Items coming into the simulation block represent box trucks full of chopped biomass that are heading to the nearest storage facility in the zone. The distance to storage, from a field to a storage facility, has a real uniform distribution between zero and the storage supply radius set by user. Items are held in this simulation block for a period of time that represents the time it takes to deliver chopped biomass to a storage facility based on travel speed. Items leaving this simulation block are box trucks that have arrived to a storage facility.

Box truck unload and bag-forming

Items coming into the simulation block represent box trucks full of chopped biomass that just arrived to a storage facility. In the beginning of the simulation and before any item is paired up with an available bag-former, the bag-formers are held for a period of time that represents preparing the bag for filling in each machine. Once a bag is in place, the box truck is paired with a bag-former for a time period that represents dumping biomass into the bag-former's apron to create silo tubes. Empty box trucks head back to fields to be paired up again with a harvester. A signal is sent that a bag-former needs to setup a new bag only when a full bag leaves the simulation block. A full bag is made up of multiple box truck loads based on the bag capacities. The MC of the bag is calculated based on a weighted average of incoming loads. Another signal is sent when all possible full bags have been sent out into the bag-sealing simulation block, this signal is to create items to represent partially full bags and send them to the bag-sealing block.

Bag seal

Items coming into the simulation block represent tube silos or bags that need to be sealed. Items are paired up with a sealing operator and held for a period of time that represents sealing a bag. Items that leave the simulation block represent sealed bags.

Bag storage

Incoming items represent sealed tube silos that are ready for storage. Items are not held for any fixed period of time in this simulation block, but the time a bag is considered to be stored is recorded. Bags will leave storage as demanded by the biorefinery.

Scale, cut and load to flatbed truck

Incoming items are divided into legal loads for transport, but held in the system based on the daily demand at the conversion facility. Enough items leave the system to fulfill the daily demand and only if a flatbed truck and a cutter-loader machine are available. The bags closest to the biorefinery are the first ones to be delivered. The loaders simulated are similar to those used by the cotton industry in Australia, which picks up the module from the ground, then straddles the semi-trailer and unloads the module onto the trailer (Simpson et al., 2002). We assumed that the loader will also weight the module in order to cut the transport unit to a length that will maximizing highway load and minimize load/unload times.

Flatbed delivery to facility

Full flatbed trucks are held in this simulation block for a period of time that represents the time to deliver modules from a storage facility in a specific zone to the conversion facility as determined by travel speed and distance. The distance to facility has a real uniform distribution between zero and the multiplication of the zone number times double the storage supply radius set by user. Items leaving this simulation block are flatbed trucks that have arrived at the conversion facility.

Module unload at facility

Items are held in this simulation block for a period of time that represents the time it takes to unload a flatbed truck at the conversion facility. Empty flatbed trucks head back to storage facilities and become available for new loads.

Delays in the BioMODS system

Delays due to weather

In IBSAL-BioMODS, the weather delays are only applicable during the mowing and harvesting operations. Similar to previous versions of the IBSAL model, our version reads the daily weather data for temperature (Celsius), precipitation (mm), snow (mm), relative humidity (decimal) and evaporation (mm). In addition to daily weather, the user specifies critical values for temperature, rain and snow for each logistic operation that would be delayed due to weather. Logistic operations are delayed by a fraction of a day, depending on the weather conditions. The daily downtime is calculated before the start of any mowing or harvesting operation. The downtime may be zero, a portion of the day or the entire day. The downtime would be the maximum between the DowntimeT, DowntimeP and DowntimeS, where: DowntimeT: If the temperature (°C) is less than the critical temperature, the delay is set to the entire working da. Otherwise, DowntimeT is set to zero. DowntimeP: rainfall (mm) of iDay divided by the critical precipitation. DowntimeS: snowfall (mm) of iDay divided by the critical snowfall. If either DowntimeP or DowntimeS are greater than one, the downtime is for the entire working day. Note that if the temperature is greater than the critical temperature and if there is no rain or snow, the downtime is zero.

Delays due to moisture content

As stated earlier, biomass may only be harvested if a harvester and a box truck are available, weather conditions are appropriate, iHour is within the in-field operations working hours and if MC (wet basis) is below a user-defined critical value and the item has not waited in queue longer than a maximum amount of days since being mowed. When the MC of a portion of a field that has already being mowed is above the critical value, a delay of an hour is placed to account for drying time. The MC is recalculated after the delay based on simulated hourly weather conditions and compared with the critical value again. This process is repeated for every item until appropriate MC is reached or the fraction of the field has being delayed for the maximum number of days.

Delays due to machine failure

Machine failures are caused by progression of time and usage. To our knowledge, there is no statistical data available regarding machine failure for the machines we considered, so we used the ASABE Standards (2011) standards to approximate our simulation values. We estimated that the mower, the forage harvester and the bag-former have similar complexities as a self-propelled combine; hence, the statistical values for machine failure would be similar. According to the ASABE Standard (2011) for Agricultural Machinery Management Data, the probability of no failures in 0.4 ha (100 acres) for a self-propelled harvester is 0.68 and self-propelled combines have about an hour of downtime for every 30 ha (70 acres) of use after the first 364 ha (900 acres) (or a downtime of 1.42 hours for every 0.4 ha). The model generates random numbers for every 0.4 ha processed through the logistic operations (mowing, harvesting or filling up a bag) that determines the probability of a failure. If a failure occurs, there is a delay with a mean of 1.43 hours and an exponential distribution. The distribution function that is considered for maintenance of machinery that is used outside of the field such as box trucks, cutter-loader, flatbed truck and unloader is the same as that in Nilsson (1999). The breakdown interval times are described by an exponential distribution with a mean of 10 hours, which implies that the machine works, on average, 10 hours between stops due to repair. The duration of each failure has a mean of 0.25 hours and an exponential distribution.

Delays due to insufficient machines available

As stated earlier in the manuscript, the mowing and harvesting processes may have a narrow window of operation in a year. The window length will depend on factors such as biomass type, the harvesting window of the major product (if it is a crop residue collection) and the weather conditions. Hence, an adequate number of available machines are key to handling all of the biomass needed for the biorefinery's yearly demand before the end of the harvest season. In addition, because in IBSAL-BioMODS the biomass collection from fields are part of a push system (which entails a desire to collect biomass as fast as we can before the end of the HP), too many mowers available can affect the total biomass collected if there are not enough harvesters and box trucks to keep up with the mowed biomass due to the maximum amount of days a mowed field can wait to be harvested. Furthermore, once a field is harvested, full box trucks deliver the biomass to the storage facility and operate along the bag-formers to fill up silo bags before it can travel back to the a field to work again with a harvester. In the same way, we would need enough flatbed trucks to supply the daily biomass demand at the conversion facility. These interdependencies make machine quantity a key input for the conversion facility to guarantee year-round availability of biomass for the conversion process.

BioMODS case study: base case scenario

Weather data, harvesting periods and critical MC (wet basis)

The progress of the harvest depends on the availability of machines, labor and local weather patterns (Sokhansanj et al., 2008), but the main factor on the length of the HP (HP) is local weather conditions (Judd, 2011). Two types of biomass and three different locations in the US were investigated: CS in Burleson County, TX and in Story County, IA and; SW in Story County, IA and in Anderson County, TN. CS collection starts at the same time as the HP for corn grain (CS is available following grain harvest), but it can last two weeks longer than the HP for the grain. The USDA statewide 5-year averages of historical weekly harvest progress were used to set the harvest season for corn in IA of

September1 to December 31 (114 days). Because TX corn harvest dates vary across the state, local experts were used to determine central TX harvest dates of July 15 to August 31(48 days). Typically one harvest per growing year maximizes SW yields, and harvesting after killing frost ensures stand productivity and persistence given that the plant is a dormant state after the hard freeze (US DOE, 2011). This practice allows for the SW to dry while standing and because of the low temperatures, the nutrients translocate to the roots, reducing ash content. Harvest of SW must end before the plant starts growing again. The HP used for SW was November 1 to March 31 in IA, and November 15 to February 28 in TN. Note that a simulation run in the model developed would start in July and end in June of the following year. Hence, we used consecutive years of weather data as input. We downloaded weather data for years 2004 to 2016 from the Easterwood Airport in TX, the Ames Municipal Airport in IA and the Oak Ridge station in TN. Weather station data was not available for all of the years downloaded. The total hours of delay time for each year was calculated using the following critical values: -20ºC for temperature, 12 mm of rainfall and 6 mm of snowfall. The years that would entail the most, average and least amount of delayed hours due to weather conditions in the HP were identified and are depicted in Table 10. The CS and SW yield values were retrieved from the input data used in the BT16 (US DOE, 2016), 6.36 DMg ha^{-1} and 11.41 DMg ha^{-1} (2.836 and 5.089 tons acre^{-1}) of CS in TX and IA, respectively and 12.88 DMg ha^{-1} and 14.42 DMg ha^{-1} (5.747 and 6.432 tons acre^{-1}) of SW in IA and TN, respectively. The MC of biomass will also depend on local weather conditions. We assumed that CS in TX and IA had an initial MC (wet basis) of

0.25 and 0.45, respectively. The assumed MC of SW in IA and TN was as low as 0.2, given that SW will be harvested during the winter months.

Table 10 Delayed hours in harvesting period for year combinations with the most, median and least delays

Parameter	Corn stover		Switchgrass	
	TX	IA	IA	TN
HP	07/15-08/31	09/09-12/31	11/01-03/31	11/15-02/28
Total days in HP	48	114	151	106
Most delays	‘08/’09, 102 hr	‘10/’11, 292 hr	‘15/’16, 252 hr	‘11/’12, 365 hr
Median delays	‘14/’15, 55 hr	‘06/’07, 225 hr	‘09/’10, 213 hr	‘04/’05, 311 hr
Least delays	‘11/’12, 23 hr	‘05/’06, 138 hr	‘14/’15, 127 hr	‘06/’07, 213 hr
Yield (DMg ha^{-1})	6.36	11.41	12.88	14.42
Initial MC	0.25	0.45	0.20	0.20

Farm participation rate

To secure the supply of a conversion facility, the facility should provide long-term incentives for farmers to increase their participation rate. High farmer participation rate reduces the risk of supply shortage. The farm participation rate is the ratio of contracted acres to the total acres in the supply radius. Our base case scenario had 80 km and 8 km (50 and 5 miles) as maximum supply radius for the conversion and maximum supply radius of storage facilities, respectively. In other words, the fields needed to supply the conversion facility are within an area of 1,964 squared miles (1,256,640 acres). The demand at the conversion facility is 725,600 DMg (800,000 DMT) year^{-1} (either of SW or CS). At the lowest yield (6.36 DMg ha^{-1}), we would need 114,157 ha, a total farm participation rate of 22%. At the highest yield (14.42 DMg ha^{-1}), the required participation rate reduces to 10%. Research by Ebadian (2016) used a 23% participation rate for his base case scenario.

Number of machines available

Optimally, we wanted to input the minimum number of machines available that would allow us to process all of the biomass through the system. Processing all of the biomass through the system includes collecting all biomass from the fields and into storage during the HP and having enough flatbed trucks to meet the daily demands at the conversion facility. Because of the stochastic nature of the model inputs, an adequate number of machines was found as opposed to an optimal number of machines Table 11. Adequate resource quantities should take into account the complex interdependencies of the different SCh echelons. We used the output reports from the model to iteratively evaluate different resource quantities as inputs. These reports include total working hours and downtime hours per machine, total inflow and outflow mass from every logistic operation and the daily inventories at every logistic operation. The factors to calculate an adequate number of machines include that no biomass was left in field due to lack of time in the HP during a median-delay year. We assumed that a biomass could not wait longer than 14 days to be harvested after being mowed. Hence, all mowing operations should finish around 14 days before the end of the HP. Harvesting operations will ideally expand until the end of the harvest season. Enough cutter loaders, flatbed trucks and unloaders, should be available to supply the daily demand at the facility. We assumed a 10-hour working shift for in-field operations (mowing and harvesting) and a 24-hour working shift for delivery (loose biomass in box trucks and modules in flatbed trucks), bag and module formation and module unload. At simulation hour 11 bag-formers and box trucks have to wait for harvester's next working shift. The reader is referred to the user manual for further understanding of how to run simulations in IBSAL-BioMODS.

Table 11 Number of machines used for a 725,600 DMg year^{-1} demand at facility

Equipment	TX (CS)	IA (CS)	IA (SW)	TN (SW)
Mower	97	19	12	20
Forage Harvester	242	54	36	55
Box truck	275	94	64	109
Bag-former	53	24	17	27
CutterLoader	6	2	2	2
FlatBed Truck	7	7	7	7
Unloader	1	1	1	1

The adequate number of equipment was evaluated based on years that represented a median delayed hours, as these years were selected as the base case. The number of mowers, harvesters, box trucks and bag-formers needed increases as the number of days in the HP decreases. Hence, the highest number of total machines needed for transporting and handling biomass from the fields corresponds to the shortest HP, 48 days for CS in TX. Likewise, the lowest number of total machines needed corresponds to the case study with the longest HP, 151 days for SW in IA. We observed that for the case studies where the HP was over 100 days, an adequate ratio of mowers to harvesters to box trucks and bag former was 1: 3: 5: 0.1, respectively. The ratio for the case study in TX was quite different: 1: 3: 3: 0.1, respectively. This could be explained by the lower yields used for the case study in TX (6.36 DMg ha^{-1} as opposed to 11.41 DMg ha^{-1} for CS in IA). Note that the ratios given are based on the number of mowers needed. Lower yields and a shorter HP require more collection machinery; and, in this case, enough mowers and harvesters were required that the number of boxtrucks needed was the same as harvesters (they reached a level where the harvesters and boxtrucks worked at the same phase). Figure 19 depicts the total mowed, harvested, demanded and delivered DMg for a base case simulation run in TX. The figure gives a perspective of the amount of biomass needed to be mowed (in blue) and harvested (in green) in a short period of time (gray box). The figure also gives details on the hours of delay per day throughout the HP. Note that mowing processes finished 12 days before the end of the HP.

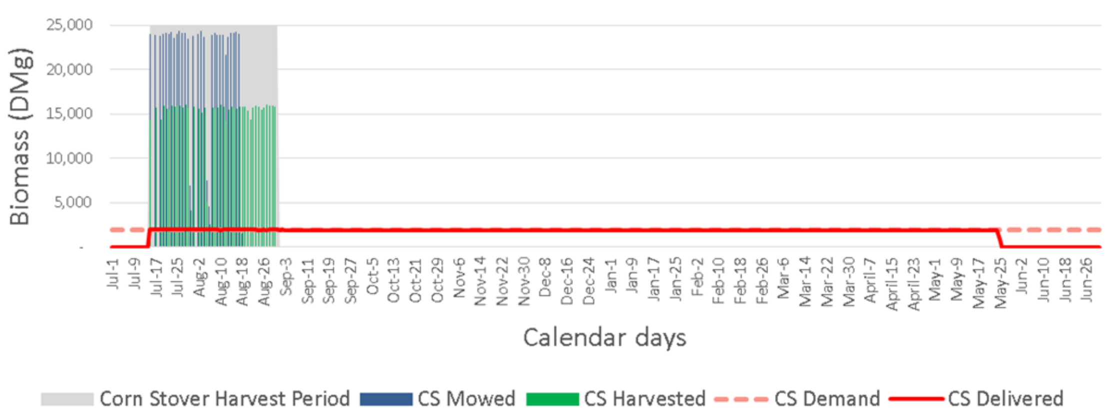


Figure 19 Biomass mowed, harvested, demanded and delivered through the year.

The IBSAL-BioMODS meets the daily demand at the biorefinery until all the biomass is consumed. Our objective was not to meet the daily demand every day in the year, but to quantify how much biomass would be available at the conversion facility given a certain supply (expressed as demand in the inputs) and how much would be lost in the process. There was no initial biomass stored considered in our runs (at any point in the SCh); hence, the model is only able to supply the biorefinery after the first day of harvest. As previously stated, the system becomes a pull process at the storage echelon, where the conversion facility pulls a maximum of 1,987 DMg (2,191 tons) day^{-1}. The capacity of the system to meet the daily demand depends on the initial supply available minus the biomass lost in the process. For instance, in the TX case study, the daily demand at the conversion facility could be met a maximum of 351 days in the simulation year, given that for the first 14 days of the simulation, no biomass is being processed. Figure 19 reflects an average of 1,683 DMg day^{-1}, 85% of the daily demand, is supplied to the biorefinery from day 15 to day 329. There was no biomass left to process in storage or anywhere upstream the SCh by day 329. Similarly, CS and SW demands in IA would only have biomass available for a maximum of 295 and 242 days in the simulation year, respectively. SW in TN is available for a maximum of 228 days per simulation year. Between 16-18% of biomass was lost in the system due to machine usage, storage lost or inefficiencies.

Specifications for equipment and other resources simulated

Table 12 describes the specifications of the machines simulated in IBSAL-BioMODS in the base case scenario. Note that the effective width used for calculating the harvester capacity was the same as the machine used immediately before (mower's width); the box truck speed was bounded to the harvester's speed while collecting biomass; and no biomass loss was considered during module delivery. Table 12 also depicts the cost and horsepower inputs used for the simulation runs in this study. The harvester is the most expensive machinery, followed by the bag-former; and, consequently, the one with the highest horsepower. One person per machine was assumed at \$15.52 $hour^{-1}$ (we used the technique by Sokhansanj et al. (2008) with inputs from USDA (2017) for the labor rate).

Table 12 Specifications for machines simulated.

Machine	Fixed Cost ($ year^{-1})	Variable Cost ($ hr^{-1})	Custom Cost ($ hr^{-1})	Specifications
Mower	1,319	25.97	31.24	New Holland speed rower 220 with tier 4B engine and Durabine 416 header. Avg. speed: 11.3 km hr^{-1} (7 mi hr^{-1}). Front width: 4.9 m (16ft). Windrower width: 1.2 m (4 ft). Field eff. and the machine eff.: triangular distribution with min, max and most likely: 0.7, 0.85 and 0.8 and 0.9,1 and 0.95, respectively (ASABE, 2011). Biomass loss: 5%. HP: 210.
Harvester	18,907	214.05	236.67	Width: 4.9 m (16ft). Avg. speed with a triangular distribution between 2.4- 9.7 km hr^{-1} (1.5-6 mi hr^{-1}) and a most likely value of 5.6 km hr^{-1} (3.5 mi hr^{-1}). Field eff. and machine eff.: triangular distribution with minimum, maximum and most likely values of 0.6, 0.85 and 0.7 and 0.6, 0.85 and 0.7, respectively (ASABE, 2011). Biomass loss: Rotz (1995) equations. HP: 598.
Box truck	5,630	66.16	59.52	Meyers 8122RT forage box with a 4.3 m (14ft) extension. Loading volume: 36 m^3 (1,280 ft^3). Legal gross weight: 14.5-Mg (16-ton). Avg. traveling speed: 81 km hr^{-1} (50 mi hr^{-1}). Travel eff.: 0.85. Winding factor: triangular distribution between 1.1 - 1.25 and a most likely value of 1.2. Bulk density: 128 kg DM m^{-3} (8 lb ft^{-3}). Biomass loss during delivery: 0.5%. Unloading time: triangular distribution between 3- 6.4 and a most likely value of 4.5 min. HP: 350
Bag-former	12,166	130.69	142.07	Bag dimensions: 152 m x 2.4 m x 3 m (500 ft x 8 ft x 10 ft). Time to load an empty bag on bag-forming machine tunnel: 10 minutes. Biomass loss during bag-forming: 3%. Biomass density in bag: 240 kg DM m^{-3} (15 DM lb ft^{-3}). 6 m (20 ft) of the bag length is lost due to tying purposes (3m at each end of the bag). Time required removing bag from bag-former and sealing bag: 10 minutes. Bag cost: $6.13 DMg^{-1} ($5.56 ton^{-1}). Sealing cost: $75 per bag. Biomass loss during storage: 0.05% loss per month. Storage costs included a fixed land charge of $625 ha^{-1} ($250 acre^{-1}). HP: 305.
Cutter-loader	6,965	93.71	101.67	Cut, load and weight time: 15 minutes. Biomass loss during module creation: 2%. HP: 120.
Flat-bed truck	4,482	27.00	28.6	Legal load: 14.6 m x 2.6 m x 3 m, 22 Mg (48 ft x 8.5 ft x 10 ft, 48,000 lb). HP: 450
Unloader	6,965	93.71	101.67	Unloading time: 5 minutes. Biomass loss during unload: 2%. HP: 120.

Results

Processing times

As expected, the amount of mass processed increased as yield increases. Table 13 suggests that 27.2 DMg of biomass would be processed in an hour; hence, with a working shift of 10 hours per day, 725,600 DMg could be processed in 2,667 days by one mower. Consequently, we would need 79 mowers to finish processing all biomass 14 days before the end of the CS HP in TX. But, this calculation does not include the stochastic components of the system, such as field and machine efficiency, varying yields, etc. Furthermore, calculating the number of harvesters, box trucks, and bag-forming machines is less straightforward, given the interdependencies stated earlier and the up-stream biomass production dependencies at each stage of the SCh. The simulation model helps understand and quantify these dependencies. Nevertheless, the values in Table 13 are useful to get an idea of the number of machines required in the SCh.

Table 13 Average processing capacity for logistic process that require machines

Logistic processes	Average processing capacity (DMg hour^{-1})			
	TX(CS)	IA(CS)	IA(SW)	TN(SW)
Mow and windrow	27	43	47	68
Forage harvester and box truck load	8	14	15	22
Box truck delivery to storage	31	32	32	34
Box truck unloading and bag-forming	54	56	56	56
Loader, scale, cutter and flatbed truck	65	65	66	66
Flatbed delivery to facility	10	15	16	17
Module unload at facility	205	207	208	207

Ownership and custom cost alternatives

Table 14 presents the cost (\$ DMg^{-1}) found at each level of the SCh for both managing alternatives: equipment ownership and custom equipment. Field setup was omitted as we did not include the cost of nutrients and land preparation in our base case. Fixed cost of owning box trucks and flatbed trucks are considered in the first process that the machines are used (logistic processes 3 and 8). No difference in price was expected between managing alternatives for operations 6 and 7. Logistic process 6 included sealing cost, bag cost and sealing operator labor hours. Storage input values for land charges were the same for both alternatives. Table 14 shows that the least-cost alternative is to own the mowers, cutter-loaders, flatbed trucks and unloaders and to custom or rent the harvesters, box trucks and bag-forming machines given their high capital cost. This management alternative would lead to logistic costs as low as \$61.05 and \$41.86 for CS in TX and IA; and, as low as \$39.42 and \$36.52 for SW in IA and TN. An argument can be made that 725,600 DMg $year^{-1}$ might be too high; hence, a demand of 362,800 DMg (400,000 DMT) $year^{-1}$ was evaluated and an increase in cost between 1-3% under the ownership management was observed.

Table 14 Ownership and custom cost for delivering 725,600 DMg year^{-1} (\$ DMg^{-1}).

	Ownership cost				Custom cost			
Logistic Process	**TX (CS)**	**IA (CS)**	**IA (SW)**	**TN (SW)**	**TX (CS)**	**IA (CS)**	**IA (SW)**	**TN (SW)**
2	$1.84	$0.97	$0.87	$0.78	$1.86	$1.05	$0.96	$0.83
3	$48.42	$24.35	$21.59	$19.96	$41.04	$23.11	$21.03	$18.33
4	$4.97	$3.38	$3.09	$3.45	$2.37	$2.35	$2.33	$2.30
5	$7.64	$5.39	$4.96	$5.55	$4.24	$4.17	$4.15	$4.14
6	$5.98	$5.98	$5.98	$5.98	$5.98	$5.98	$5.98	$5.98
7	$0.13	$0.13	$0.13	$0.13	$0.13	$0.13	$0.13	$0.13
8	$2.40	$2.34	$2.33	$2.34	$2.47	$2.46	$2.44	$2.45
9	$3.04	$2.80	$2.58	$2.50	$3.16	$2.91	$2.67	$2.59
10	$0.01	$0.01	$0.02	$0.02	$0.79	$0.78	$0.78	$0.78
Total	**$74.43**	**$45.35**	**$41.55**	**$40.70**	**$62.04**	**$42.94**	**$40.46**	**$37.53**

Corn stover and switchgrass in IA

To evaluate the effects on price per DMg when sharing equipment resources among biomass types, we evaluated the collection and delivery of 725,600 DMg of CS and 725,600 DMg of SW in IA for the same simulation year. Given the two-month overlap among the HP for the different biomass types (November and December), the adequate number of machines needed for in-field operations was found to be slightly greater than the number of machines needed to collect and deliver CS to storage facilities in IA. But, the number of machines involved in meeting the biorefinery's daily demand was doubled. For this scenario we simulated 19 mowers, 57 forage harvesters, 101 box trucks, 28 bag-formers, 4 cutter-loaders, 14 flatbed trucks and 2 unloaders. Some resources are shared between biomass types in the HP overlap. Sharing resources among biomass types in IA resulted in a total cost of $39.80 per DMg (a 5% cost reduction than when managing CS alone).

Sensitivity analysis

Weather conditions

The number of equipment found to be adequate for years that represented a median number of delayed hours in the HP was the input to all the sensitivity analysis runs. We evaluated the performance of the system with weather inputs that represent low and high delays in the HP. We anticipated that weather values that translate to higher hours of delay in the HP entailed lower biomass delivered at the conversion facility given that biomass would be left in field by harvesters due to lack of time. In TX, the year with highest delays had 85% more delayed hours than the median (Table 10), which caused a 13% reduction in total delivered biomass to the conversion facility. Simulating years with the highest delays in our database for the states of IA and TN only reduced the total delivered biomass by 2%. This impact can be explained by the lower variability between years with median and high delays (17-30%) and the longer HP in these states.
Lower hours of delay caused that all the field operations are completed before the end of the HP. In TX, field-operations terminated 5 days earlier and there was a cost reduction of 6%. In IA, a cost reduction of 1% and 2% were observed for CS and SW,

respectively. On average, field-operations in IA were terminated 8 days earlier. A cost reduction of 1% was observed in TN and field operations were terminated 9 days earlier.

Shorter harvesting period

To evaluate the sensitivity of the HP length, we reduced the range by 10, 20 and 30% by moving the start of the HP to a later start date. The HP used are presented in Table 15. We anticipated that biomass left in field (by harvesters or mowers) increases as the HP is reduced. We observed that the total biomass left in field increased from 6% to 25% to 31% when reducing the HP in TX by 10, 20 and 30%, respectively. The total biomass left in fields was not as high for the other case scenarios: 5% when HP is reduced by 10% and between 5-13% when reduced by 20 or 30%.

Table 15 Sensitivity analysis on the harvesting period

Scenario	HP decrease	HP	Total Days	Biomass left in field (DMg)	Percent Biomass left in field
TX (CS)	10%	07/20-8/31	43	50,502	6%
	20%	07/25-8/31	38	201,748	25%
	30%	07/30-8/31	33	251,156	31%
IA (CS)	10%	09/20-12/31	103	39,935	5%
	20%	10/01-12/31	92	87,780	11%
	30%	10/12-12/31	81	71,326	9%
IA (SW)	10%	11/16-03/31	136	38,545	5%
	20%	12/01-03/31	121	60,131	8%
	30%	12/16-03/31	106	41,415	5%
TN (SW)	10%	11/26-02/28	95	41,972	5%
	20%	12/06-02/28	84	87,818	11%
	30%	12/17-02/28	73	105,177	13%

Mower and harvester speed

In the base case scenario, the mower speed was double the speed of the harvester. We estimated that the power of the harvester was being underutilized due to the relative low yield, since we are mostly bounded by the speed of the harvester. Hence, we evaluated the base case scenarios with a speed mower 50% less from the base case and a harvester double the speed than the one used in the base case. Total costs of delivering biomass under the different speeds are presented in Table 16. Reducing the mower speed by 50% caused a cost increase between 1-9%. Increasing the harvesters made the highest impact on unit cost of biomass. On average, ownership and custom cost was reduced by 27% and by 31%, respectively. The cheapest biomass unit was SW in TN at $26.99 when the harvester speed and the mower speed were 11.3 km hr^{-1}.

Higher yields

Higher yields were evaluated to analyze the effect on cost. The higher yields used in the study for CS and SW yield values were retrieved from the input data used in the BT16 (US DOE, 2016). The higher yield values used for CS in TX and IA were 6.6 and 11.9 DMg ha^{-1} (2.92 and 5.24 tons $acre^{-1}$); and for SW in IA and TN were 13.3 and 18.1 DMg ha^{-1} (5.85 and 7.9893 tons $acre^{-1}$). Higher yields decreased price by 2%-12%.

Table 16 Costs from sensitivity analysis on biomass yield, mower and harvester speed ($ DMg^{-1})

Scenario	Ownership cost				Custom cost			
	TX (CS)	IA (CS)	IA (SW)	TN (SW)	TX (CS)	IA (CS)	IA (SW)	TN (SW)
Base case	$74.43	$45.35	$41.55	$40.70	$62.04	$42.94	$40.46	$37.53
Higher yield	$73.04	$43.67	$39.64	$36.52	$60.66	$41.18	$38.47	$33.10
Slower Mower	$79.71	$49.62	$42.83	$42.21	$63.19	$43.99	$40.93	$37.78
Faster Harvester	$52.64	$33.23	$29.69	$30.67	$39.29	$30.21	$28.01	$26.99

Conclusions

With an additional grower payment $ 29.77 DMg^{-1}, the BioMODS logistic costs in the base case scenario were estimated at $90.82 and $71.63 for CS in TX and IA; and, $69.19 and $66.29 for SW in IA and TN. The BioMODS system met the goal of $88.2 DMg^{-1} (DOE, 2014a); with exception of the TX case study that was over by only 3%. Table 17 presents logistic cost found in this one and similar studies. When comparing CS prices with AGCO and FDCE, the BioMODS system was more cost-efficient for IA, but not for TX. When combining AGCO's single-pass harvest system and FDCE's equipment for collection and bale transport, the BioMODs system is also more cost-efficient in IA; unless a bale density of 225 kg m^{-3} can be consistently achieved by the AGCO and FDCE system combination. The logistic costs presented in the TennEra study were higher than the values for SW in IA and TN presented in this study.

Table 17 Cost comparison of the BioMODS with DOE studies

Feedstock	Logistic system	Logistic
Corn stover	BioMODS (TX)	$61.05
	BioMODS (IA)	$41.86
	AGCO (177 kg m^{-3})	$54.48
	AGCO (201 kg m^{-3})	$51.79
	FDCE (177 kg m^{-3})	$54.84
	FDCE (225 kg m^{-3})	$51.79
	AGCO + FDCE	$45.93
	AGCO + FDCE* (225 kg m^{-3})	$34.46
Switchgrass	BioMODS (IA)	$39.42
	BioMODS (TN)	$36.52
	TennEra	$55.15

Tube silos cannot be stacked and therefore may be considered inefficient with respect to land area needed for storage, especially compared to large bale stacks (which are themselves saddled with issues like stability and fire risk). However, the differences in footprint needed for storage of tube silos might be significantly less than storage needed for a stacked bale system. Our analysis suggests that the stacked bale and tube silo systems would require roughly 1 and 3 ac of storage, respectively, per 1000 ac of biomass production. Staff from Abengoa Bioenergy Corporation, LLC communicated that bales (0.9 m high, 1.2 m wide and 2.4 m long – or 3ft. x 4ft. x 8ft.) are stacked 6 bales high, 6 bales wide and 120 bales long. Two stacks of bales are separated by 18 m (60ft) in storage, and 37 m (120ft) apart from the next two stacks of bales. Assuming that stacks across from each other would be 18 m too, and at a density of 160 kg m^{-3} (10 DM lbs ft^{-3}), we calculated that bale storage needs 6.76 m^2 for every stored DMg (66 ft^2 for every stored ton). Under the BioMODs system, tube silos are expected to be 3 m high, 2.4 m wide and 146 m long (10ft. x 8ft. x 480ft.) with a stored density of 240 kg m^{-3} (15 DM lbs ft^{-3}). In storage, tube silos would be placed 1.2 m (4 ft) between each other and 3 m (10ft) between tube silos that are across from each other. This translates into 2 m^2 for every stored DMg (20 ft^2 for every stored ton), 69% less storage area needed when compared to the bale system.

We acknowledge that there are various limitations to the developed IBSAL-BioMODS. SW collection might not involve a mower machine when harvested during the winter months, but we wanted to include the analysis of SW in our simulation runs using a consistent machinery set. In IBSAL-BioMODS, mowing and harvesting speed does not reduce with higher yields. The model does not use or output geographical data or distances from fields to fields. The model only simulates distances from conversion facility to storage and from storage to fields. Roundtrips for box trucks and flatbed trucks are based on these distances. Finally, ash content was not measured in this system.

CHAPTER V

CONCLUSIONS

DOE has estimated herbaceous biomass availability through simulations with the Policy Analysis System (POLYSYS) agricultural modeling framework. Operational assumptions for POLYSYS limited conversion of pastureland to perennial grass crops to counties east of the 100th meridian as a proxy for precipitation sufficient for economically viable yield, but allowed cropland conversion regardless of location. Knowledge of local conditions raised questions about predicted biomass quantities for TX counties in the 2011 assessment. POLYSYS was rerun with different assumptions, specifically replacing the 100th meridian boundary with average annual precipitation data and limiting cropland conversion in low rainfall counties. Perennial grass production was found to be overestimated by 8% and 87% in the US and TX, respectively (at \$66.14 DMg^{-1}), when limiting all land conversion to regions with precipitation greater than 635 mm. Total herbaceous biomass predicted was approximately the same as in the BT2, but the biomass geographical location changed across the nation. TX' biomass contribution reduced from 6% to 1% at \$66.14 and 16% to 11% at \$88.18. Subsequent to this research being conducted, DOE released the 2016 biomass inventory assessment, and these results are compared to those newest estimates.

While sufficient biomass has been identified to meet the Renewable Fuel Standard (RFS2) targets by previous studies, availability does not equal access. Our objective was to quantify the potential accessible and stranded herbaceous biomass from different scenarios of predicted available biomass in both TX and the US. The location and size of potential biorefineries and depots was determined using the geographic location of suitable lands for biomass, the transportation infrastructure and published economic constraints for minimum biomass supplied to a facility within a specified neighborhood. Our GIS-based heuristic addresses the capacitated facility location problem by distributing potential biomass along a county's suitable lands. Road and rail proximity optionally was included in the algorithm. The total stranded biomass in TX was 28% of the total available biomass. Including the constraint of the transportation network accessibility (rail and appropriate roads) when determining facility location increased the total stranded biomass to 33%. Using county centroids as supply points and potential facilities led to an increase of 7% in total biomass captured by all facilities in TX when compared to our raster-based heuristic. The nationwide accessible biomass is 90% of the available biomass, 78% of which is captured by biorefineries. In total, 77 biorefineries and 171 depots were identified in the US, which projects to 184 million Mg year^{-1} delivered to biorefineries and depots, or 65.3 billion liters of advanced biofuels, more than the targeted 60 billion liters of advanced cellulosic biofuel in the RFS2.

Most biomass feedstock systems focus almost exclusively on dry bales; however, bale systems have not reached critical adoption due to logistic and economic limitations, such as bulk density. Biomass bulk density has a major impact on storage and transportation costs; harvest and transportation labor requirements; and biorefinery capital cost, energy requirements and material handling and processing complexity (Hess et al., 2007; Sokhansanj and Turhollow, 2002). But, since densification requires an unrecoverable energy investment, unavoidably reducing the net energy gain, densification should be no greater than needed to achieve minimum total logistics cost. Desirable characteristics of a low-cost biomass logistics system would include independence of strict moisture and weather conditions; minimal non-value-added operations; weight-limited transport that maximizes dry matter shipped per load; rapid loading and unloading with little labor input; and distributed, highly-flexible, strategically located storage. We analyzed a supply chain system that collects biomass with a wide range of crop moistures; anaerobically stores biomass in tube silos; creates transport units of varied length (length is chosen to optimize shipping volume and weight limits based on the moisture and density achieved in the tube silo) as needed by the industry and loaded on a truck; maintains the as-stored density throughout transport to the point of consumption; and thus minimizes transport costs and eliminates the need of re-densification. The system was defined as the BioMass Optimized Delivery System (BioMODS). We developed a simulation model to represent the behavior of the BioMODS system and analyzed the delivery of CS in TX and IA and of SW in IA and TN. Considering a grower payment of \$ 29.77 DMg^{-1}, the BioMODS logistic costs in the base case scenario were estimated at \$90.82 and \$71.63 for CS in TX and IA; and, \$69.19 and \$66.29 for SW in IA and TN. The BioMODS system met the goal of \$88.2 DMg^{-1} (DOE, 2014a); with exception of the TX case study that was over by only 3%. The BioMODS system was projected to be more cost-effective than the DOE examined alternatives, with an exception of the case study in TX.

Future research

We believe that future analyses by DOE should include bounding land conversion of cropland to perennial grasses by the average annual precipitation. This boundary inclusion may not have a high impact on the total biomass predicted in the US, alike our results, but the geographical location of biomass production may change. Alternative market radius for biorefineries and depots could be applied to the GIS-based heuristic presented in this dissertation to explore different possibilities. In addition, different facility economic sizes would help understand the different possibilities for an emerging bioenergy industry. In this study, the potential consolidation of biomass production into more concentrated areas as a result of established contracts between landowners and biorefinery investors was omitted. The study assumes that agricultural products that are potential feed for a biorefinery are crops distributed among other crops in land types classified as cropland and pastureland as of the NLCD of 2011. Future research should include an updated NLCD, such as the 2016 NLCD; and, the variation of land utilization between the new and old rasters should be included in the analysis of the biorefinery industry.

Furthermore, the likely structure of the bioenergy supply chain could be studied without the assumption that a biorefinery would be able to take various types of biomass. And, instead, apply the facility location problem solution presented in this dissertation for the different types of biomass. A more holistic approach could include a constraint that a biorefinery should be located within a certain distance to a blending facility; or, within a certain distance from the consumers.

The GIS model developed in this study could be extended to the analysis of different industries such as byproducts from the agricultural feedstock. In fact, the model is not limited to the agricultural-based energy industry; the model could be applied to the analysis of the supply chain of various other industries.

The overall goal of the discrete-event simulation model presented in this manuscript was to design and schedule a highly constrained biomass supply chain of an experimental module-based biomass collection system to meet the daily biomass demand of a commercial-sized biorefinery at the minimum delivery cost possible. While the model was good at assessing the relative performance and delivered cost of an experimental module-based biomass collection system in comparison to commercially available alternatives, the model is limited by the modeler's intentions. A comparison of the IBSAL-BioMODS and the IBSAL-MC is presented in the following paragraphs in addition to the limitations of the models.

IBSAL-BioMODS was designed assuming that the user inputs a desired daily demand at the biorefinery. This value is used to calculate the amount of fields to be created in the system and that would supply the biorefinery. In contrast, IBSAL-MC lets the user input a database of crop fields with different attributes to feed a biorefinery. Either approach could be easily applied to either of the IBSAL versions depending on the user's requirements. A clear limitation of the IBSAL-BioMODS is that the daily demand at the biorefinery would be met until all of the biomass in the system has being processed. This could be addressed by creating a buffer in the code when calculating the total amount of fields that would be supplied by a biorefinery.

IBSAL-MC has the capability of automatically replicating a simulation a specific amount of times. This capability was removed in IBSAL-BioMODS because of the intended reporting per replication by the modelers. IBSAL-BioMODS records and reports the attributes and changes in attributes of every simulation item as it goes through the system. This data recording and reporting prolonged the running time per replication; hence, the capability was removed.

As per the author’s knowledge, the version presented in this dissertation and all the previous versions of IBSAL lack of spatial data regarding the location of fields, storage facilities and biorefineries. Future research might include merging the results from the GIS-based heuristic and the simulation model presented in this dissertation. The geolocation information would improve the system analysis as the model could potentially calculate the distances between fields, storages and the biorefinery. Knowing these distances would incorporate a more efficient network flow analysis between fields, storages and the biorefinery; and, hence, better cost estimations.

As per the author’s knowledge, the IBSAL models still need to be validated with field experiments. Additional improvements to the IBSAL-BioMODS model include the addition of a mixed-integer programming model to find the optimal number of machines as input to the model. Reports could be presented in a more database friendly software than Excel, if the ExtendSim software expands this capability. The model schedules the supply chain for only one commercial-sized plant and should be extended to meet the demand of several plants. In addition, the model lacks consideration of correlations between some of the input parameters. For example, the correlation between the harvester speed and the production yield at a field is neglected.

In addition, the documentation of changes or extensions made to the IBSAL model would be beneficial for future researchers. From the author's perspective, this documentation would accelerate the learning process of the model and increase the application of the model to diverse agronomic supply chain systems. The discrete-event model presented is not limited to production of biofuels; the model could be applied to other bioenergy products such as electricity or heating.

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APPENDIX

IBSAL-BIOMODS USER MANUAL

Overview

The model is composed of an ExtendSim file and a Microsoft Excel file where the simulation outputs are reported. Both files should be in the same windows folder for the model to run appropriately. Parameters for the model can be edited through the textboxes in the main user interface or through the buttons to access the input databases in the main user interface: equipment specifications, daily weather and fields tables. The main interface illustrates the flow of the system evaluated, some of the cost, site, resource and biomass parameters that can be modified in the model, and the daily working hours used in the model for the different logistic operations (identified by the attribute called row). The user can access the input databases to further modify parameter values in the model. Once the user has input/edit the parameters as desired, the model should be run by clicking the "Run IBSAL" button on the right bottom corner of the main user interface.

Input Databases

The values presented in the tables represent the default values in the model and the baseline scenario for this study. Any of the values in the input databases can be changed to be random values as opposed to a deterministic value. Triangular (x,y,z) refers to a triangular distribution with a minimum value of x, a maximum of value of y and a most likely value of z.

Table 18 Fields

Input	Description	WS	SW	CS
Biomass type	Type of biomass	Wheat Straw	Switchgrass	Corn Stover
Biomass ID	Identifies biomass type with a numeric value	1	2	3
Biomass Demand	Biomass demand at conversion facility (tons year^{-1})	725,600	725,600	725,600
Yield	Average biomass yield (dry tons acre^{-1})	2	5.75	5.089
Yield Std. Dev.	Yield standard deviation	0.1	0.5	0.2
Start harvest month	Numeric value of month when harvest starts	05	11	09
Start harvest day	Numeric value of day when harvest starts	01	01	09
End harvest month	Numeric value of month when harvest ends	06	03	12
End harvest day	Numeric value of day when harvest ends	30	31	31
Moisture content	MC wet basis (decimal fraction)	0.25	0.7	0.45

The equipment specifications table is composed of two columns per machine. As each machine is different in types of specifications, the first column is used to describe the value needed for the system analysis and the units that the value should be in for the simulation to work properly. The second column is used to input the value.

Table 19 Mower conditioner with windrower header

Number	Description	Value
1	Width (ft)	16
2	Field speed average (mph)	7
3	Field efficiency (dec. fraction)	Triangular (0.7,0.85,0.8)*
4	Machine efficiency (dec. fraction)	Triangular (0.9,1,0.95)
5	Horsepower (hp)	210
6	Custom cost ($/hr)	31.24
7	Annual fixed cost ($)	1,319.22
8	Variable cost ($/hr)	25.97
9	Labor cost ($/hr)	15.52
10	Purchase price ($)	27,033
11	Machine biomass loss (dec. fraction)	0.05
12	Critical temperature (minimum working condition) (°C)	-20
13	Critical rainfall (mm)	12
14	Critical snowfall (mm)	6
15	Windrower width (ft)	

Table 20 Forage harvester

Number	Description	Value
1	Width (ft)	16*
2	Field speed average (mph)	Triangular (1.5,6,3.5)
3	Field efficiency (decimal fraction)	Triangular (0.6,0.85,0.7)
4	Machine efficiency (decimal fraction)	Triangular (0.6,0.85,0.7)
5	Horsepower (hp)	598
6	Custom cost ($/hr)	236.67
7	Annual fixed cost ($)	18,907
8	Variable cost ($/hr)	214.05
9	Labor cost ($/hr)	15.52
10	Purchase price ($)	340,873
11	Machine biomass loss (decimal fraction)	1
12	Critical temperature (minimum working condition) (°C)	-20
13	Critical rainfall (mm)	12
14	Critical snowfall (mm)	6

Table 21 Box truck

Number	Description	Value
1	Volume (ft^3)	1,280
2	Bulk density (dry lbs per ft^3)	8
3	Loading preparation time (min)	Normal (5.5,2)
4	Loading efficiency	0.9
5	Horsepower (hp)	350
6	Custom cost ($/hr)	59.52
7	Annual fixed cost ($)	5,629.8
8	Variable cost ($/hr)	66.16
9	Labor cost ($/hr)	15.52
10	Purchase price ($)	110,589
11	Maximum load capacity (tons)	16
12	Machine biomass loss (dec. fraction)	0.005
13	Travel speed full (miles per hour)	50
14	Travel speed empty (miles per hour)	50
15	Travel efficiency (dec. fraction)	0.85
16	Unloading time (min)	triangular (3,6.4,4.5)
17	Winding factor (dec. fraction)	triangular (1.1,1.25,1.2)
18	Critical temperature (minimum working condition) (°C)	-20
19	Critical rainfall (mm)	50
20	Critical snowfall (mm)	25

Table 22 Bag forming machine

Number	Description	Value
1	Bag Cost ($/DM ton)	5.56
2	Bag length (ft)	500
3	Bag width (ft)	8
4	Bag height (ft)	10
5	Biomass compressed density (DM lb/ft3)	15
6	Horsepower (hp)	305
7	Custom cost ($/hr)	142.07
8	Annual fixed cost ($)	12,166
9	Variable cost ($/hr)	130.69
10	Labor cost ($/hr)	15.52
11	Purchase price	219,335
12	Critical temperature (minimum working condition) (°C)	-20
13	Critical rainfall (mm)	50
14	Critical snowfall (mm)	25
15	Sealing Cost ($/bag ending)	75
16	Time required to load a bag on tunnel (min)	10
17	Machine biomass Loss (decimal)	0.03*
18	Time required to remove bag from bag former and seal bag (min)	10
19	Bag length (ft) lost due to tying purposes	20
20	Biomass loss in bag (decimal/month storage time)	0.005

Table 23 Module scale, cutter and loader

Number	Description	Value
1	Cutting time per load (min)	5
2	Cutting efficiency (dec. fraction)	0.98
3	Loading time per load (dec. fraction)	5
4	Loading efficiency (dec. fraction)	triangular (0.5,0.8,0.65)
5	Weighting time per load (min)	5
6	Weighting effciency (dec. fraction)	1
7	Horsepower (hp)	120
8	Custom cost ($/hr)	101.67
9	Annual fixed cost ($)	6,965
10	Variable cost ($/hr)	93.71
11	Labor cost ($/hr)	15.52
12	Purchase price	92,682
13	Machine biomass loss (decimal)	0.02

Table 24 Flatbed truck

Number	Description	Value
1	Legal load lenght (ft)	48
2	Legal load width (ft)	8.5
3	Legal load height (ft)	10
4	Legal load weight (lbs)	48,000
5	Load tie time- securing load (min/load)	5
6	Travel speed full (mph)	normal (66.16, 20.53) highest 90 lowest 40
7	Travel speed empty (mph)	normal (69.21, 20.53) highest 100 lowest 50
8	Travel efficiency	triangular (0.8, 1, 0.9)
9	Winding factor	triangular (1.1, 1.25, 1.2)
10	Machine biomass Loss (decimal)	0
11	Power (hp)	450
12	Custom cost ($/hr)	28.6
13	Annual fixed cost ($)	4,481.56
14	Variable cost ($/hr)	27
15	Labor cost ($/hr)	15.52
16	Purchase price	60,032.67

Table 25 Module unloader at facility

Number	Description	Value
1	Unloading time per load (min)	5
2	Efficiency Unload	triangular (0.8, 1, 0.9)
3	Horsepower (hp)	120
4	Custom cost ($/hr)	101.67
5	Annual fixed cost ($)	6,965
6	Variable cost ($/hr)	93.71
7	Labor cost ($/hr)	15.52
8	Purchase price	92,682
9	Machine biomass Loss (decimal)	0.02